Essays on Child Care and Child Development

Dissertation

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By

Sungjoon Kwon, B.A., M.A.

Graduate Program in Economics

The Ohio State University

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Dissertation Committee:

David M. Blau, Advisor

Audrey L. Light

Bruce A. Weinberg

Abstract

This dissertation consists of two chapters. In the first chapter, I analyze the effects of child care subsidy versus income transfer programs on child cognitive and non-cognitive skill development. This is an important study because of large variation across countries in the allocation of public funds for support of families between child care subsidies and cash transfer programs. I specify and structurally estimate a model of household decisions about labor supply and child care, jointly with cognitive and non-cognitive skill production functions, using data from the Longitudinal Study of Australian Children. Counterfactual simulations show that child care subsidies have a positive effect on cognitive skill, and a negative effect on non-cognitive skill. The simulations show that income transfers improve both types of skills, but the effects per dollar of government expenditure are smaller than the effects of child care subsidies. The results also suggest that child care subsidies are more effective in improving children's skills when they are used for low income families, and that imposing a maternal work requirement is important for income transfers to be effective for improving child skill development.

In the second chapter, I study the effect of non-maternal childcare time on children's cognitive achievement, using data from the Child Development Supplement of the Panel Study of Income Dynamics. Using a specification that carefully distinguishes non-maternal child care and maternal work, I find sizable negative effects of non-maternal childcare, resulting mainly from use of informal childcare when children are very young. However, the negative effect of non-maternal childcare can be at least partially offset by the positive effect of maternal work and the positive effect of income from maternal work. The results also show that children in low income families have a negative impact of maternal work, and the adverse effects of non-maternal childcare and maternal work cannot be offset by the positive impact of income from maternal work. Finally, I show that controlling for maternal work results in a 43% increase in the negative effect of non-maternal child care.

Dedicated to my wife, Eunji Lee.

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Vita

October 13, 1984 .... Born - Busan, South Korea

2011 .... B.A.A.
Korea University

2011 .... B.Ec. Statistics
Korea University

2013 .... M.A. Economics
Korea University

2014 .... M.A. Economics
The Ohio State University

2014-2019 .... Graduate Associate
The Ohio State University

Fields of Study

Major Field: Economics

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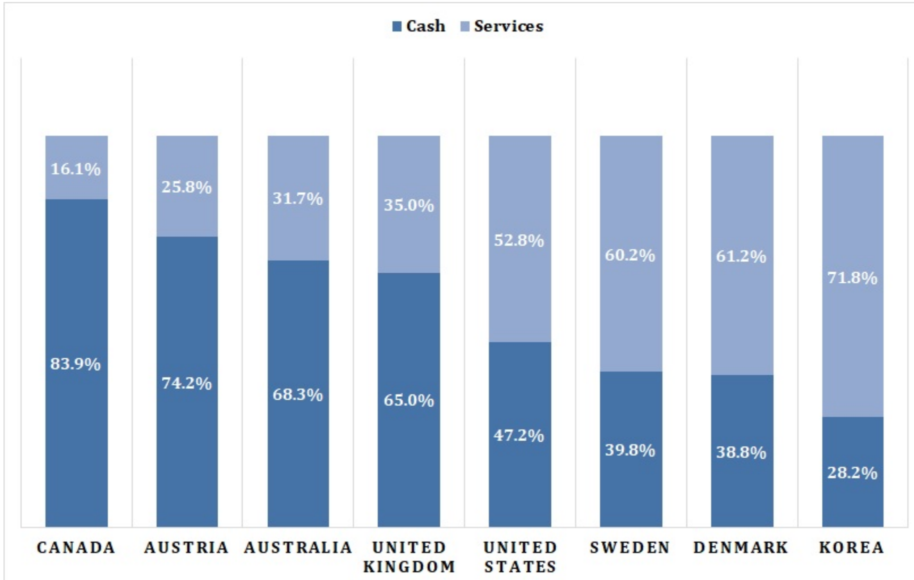
1.1 Introduction

Many countries spend extensive public resources on programs that support families with children. In 2016, the United States federal government spent about 486 billion USD on programs, services, and tax expenditure for children. This represents around 2.1% of the US gross domestic product (GDP).[1] Some countries spent an even greater share of their GDP on policies for families with children than the US.[2] The allocation of public funding between cash transfers and in-kind services varies substantially across countries. Figure 1.1 shows the allocation of public funding for benefits for families with children for eight selected countries of the Organization for Economic Cooperation and Development.[3] In 2013, Canada, Austria, Australia, and the United Kingdom spent 65% to 84% of public funding on cash (or income) transfers, with the rest spent on in-kind services such as child care subsidies and early childhood education. However, the United States, Sweden,

[1]See Isaacs, Lou, Hahn, Ovalle and Steuerle (2017).

[2]In 2013, Denmark, France, Hungary, Iceland, Luxembourg, Sweden, and the United Kingdom each spent more than 3.5% of their GDP. See the Organization for Economic Cooperation and Development family database (http://www.oecd.org/els/family/database.htm).

[3]In the original data, public spending on family benefits is categorized into three types: (1) child-related cash transfers to families with children, (2) public spending on services for families with children, and (3) financial support for families provided through the tax system. I combine the first and third categories into one group.



Source: OECD Family Database
Note: "Cash" includes child allowances, income support, tax exemptions, child tax allowance, and child tax credits. "Services" includes subsidization of child care, early childhood education facilities, and public child care support. Programs that assist families, but not exclusively families with children, such as health and housing support, are not included.

Figure 1.1: Share of Public Expenditure on Cash Transfers versus In-Kind Services in 2013

Denmark, and Korea spent a greater share of public funding on services (53% to 72%) than on cash transfers.

The large variation across countries in the share of public funds allocated to cash transfers versus in-kind services for children raises an important question: What are the effects of cash versus in-kind programs on the outcomes targeted by these programs?[4] This study addresses this question in a specific context: the effects on child cognitive and non-cognitive

[4]Another interesting and important question is, can the variation across countries be explained in terms of differences in the goals of these programs? However, this question is beyond the scope of this study because it requires a cross-country analysis with comparable data across countries.

skill development of child care subsidies versus income transfers in early childhood. Cognitive and non-cognitive skills are important outcomes[5] because they are key determinants not only for human development in childhood but also for adult outcomes, such as educational attainment, employment, and earnings.[6] In this study, I focus on programs for preschool age children. This period is important because returns to investment in the early stage of childhood are greater than in later stages of childhood.[7] In addition, children require intensive care at young ages, so public support for families is crucial at these ages. I consider a specific type of in-kind program: child care subsidies. Child care subsidies play an important role in early childhood because they directly help families pay for child care. Moreover, many countries use them to stimulate child development for improving school readiness and future well-being.[8]

Many previous studies have evaluated the effects of child care subsidies and income transfers on child outcome measures, but differences in the outcomes, methods, target population, and the specific features of these programs make it difficult, if not impossible, to use existing results to compare the effects of these two types of programs. For example, child care subsidy programs are generally directed at preschool age,[9] while recent papers that study the effect of family income analyze children at older ages.[10] The skill development

[5]Some examples of cognitive skills are verbal ability, spatial perception, memory, and understanding. Examples of non-cognitive skills are empathy, self-esteem, self-control, and social ability.

[6]Bernal and Keane (2011), Cunha and Heckman (2007, 2008), Cunha, Heckman and Schennach (2010), Heckman and Mosso (2014), Heckman, Stixrud and Urzua (2006)

[7]Cunha and Heckman (2008), Cunha et al. (2010), Heckman and Mosso (2014)

[8]Early intervention programs, such as Head Start, are intended to stimulate child development. Such programs can be thought of as a subsidy for high quality child care.

[9]For example, Baker, Gruber and Milligan (2008) examine the effects of a universal child care subsidy in Québec, Canada, which is directed at ages 0 to 4, and Herbst and Tekin (2016) evaluate the effect of subsidy receipt in the year prior to kindergarten.

[10]For instance, Dahl and Lochner (2012) focus on children aged 5 to 14, and Akee, Copeland, Keeler, Angold and Costello (2010) and Akee, Copeland, Costello and Simeonova (2018) consider children aged 9 and above.

process at younger ages is likely to be different from the process at older ages. Hence, it is unclear how useful it is to compare the results across studies analyzing children of different age groups. In addition, comparing the effects of the two types of programs is difficult because they often have different eligibility restrictions, such as a parental work requirement and family income tests. These restrictions are determined based on how the population of interest is defined. A transfer program could be highly targeted to a specific group, such as children in extreme poverty, or could be universal, with the intent of improving the outcome for all children. Therefore, each program could target a different eligible group of the population,[11] so comparing the effects of programs with different eligible groups may confound differences in program effects with differences in effects across groups.

This study analyzes the effects of child care subsidies versus income transfers on child cognitive and non-cognitive skills in a framework that allows direct comparisons of the effects for a specific age group and set of program restrictions. I accomplish this goal by specifying and structurally estimating a model of family decisions regarding employment, child care, and the allocation of resources to children, jointly with the technology of cognitive and non-cognitive skill production. The analysis is designed to provide implications for policy makers to make informed decisions on how to allocate public resources between cash transfer and child care subsidy programs for the goal of improving child skill development.

The following features of the model allow me to accomplish the aforementioned goal. Parents face several key tradeoffs in the model. They care about their own consumption and leisure, and also about their children's cognitive and non-cognitive skills. They face a budget constraint that dictates that every additional dollar spent on their own consumption

[11] For example, in the US, to receive the Earned Income Tax Credit (EITC), a household must have earnings from work and meet an income test. The EITC generally benefits children in low to middle income families with a working parent. The eligibility requirements for Head Start include no work requirement, but family income must be below the federal poverty guideline, so children in low income families primarily benefit from Head Start.

requires spending one dollar less on resources invested in child skill development. Parents also face time constraints: a family must use non-maternal child care including father's child care in order for the mother to have more hours of work or leisure. There are two ways to spend family income on children: non-parental child care and other monetary investment, where the latter is any child-related expense other than the cost of non-parental child care.[12] Parents have two non-parental child care options: formal child care, which meets the government's standards and requirements,[13] and informal child care, which is provided by relatives and non-relatives,[14] with different hourly prices for each type of non-parental child care. Finally, parents face technological constraints in the form of dynamic skill production functions that depend on hours of parental and non-parental child care, monetary investment, and the current skill levels. The technology of skill production differs across skill types, so a unit of a given input may have different marginal effects on child cognitive and non-cognitive skills.

A key feature of the model is that the budget constraint explicitly incorporates the existing Australian child care subsidies (Child Care Benefit and Child Care Rebate) and income transfers (Family Tax Benefit and Parenting Payment). The budget constraint accounts for the different eligibility restrictions based on family income and maternal work for each program. In the model, parents are assumed to allocate their resources conditional on these existing programs, giving rise to potential labor supply and child care demand responses to the programs.

The model features discussed above allow a realistic representation of how parents allocate their time and family income, and create key channels through which child care

[12]For example, books, toys, and educational or recreational activities.

[13]For example, center-based child care and family day care.

[14]For example, grandparents, friends, and nannies.

subsidies and income transfers affect child skill development. This makes the model informative about the role of policy in determining parental decisions on labor supply, child care and inputs to child skill production, and the resulting skills of children.

To estimate the model, I use data from the Longitudinal Study of Australian Children (LSAC). The LSAC is an ongoing longitudinal survey that follows the development of a representative sample of children from all parts of Australia. This study has collected very rich information about the children's cognitive and non-cognitive skills, child care arrangements, family demographics, and parents' income, starting at the time of a focal child's birth. The LSAC also contains measures of hours spent by the child with his or her father, hours in each non-parental child care arrangement, and parents' hours of work.

The estimated model captures the main patterns of the data reasonably well. The model accurately predicts the patterns of extensive margins for parental choice variables: maternal work, paternal child care, formal child care, and informal child care. In addition, the model closely captures the distribution of hours of each choice variable.

Using the estimated model, I simulate the effects of child care subsidies and income transfers for children aged 0 to 5. Counterfactual simulations show that child care subsidies have a positive effect on child cognitive skill development, but a negative effect on non-cognitive skill development. Compared to the benchmark with no child care subsidy and no income transfer, a 100% subsidy for formal child care at ages 0 to 5 with no restriction (i.e., universal formal child care) improves the average cognitive skill at ages 10 to 11 by 0.0111 standard deviations, but reduces the average non-cognitive skill by 0.0113 standard deviations.[15] These effects are mainly driven by a significant increase in use of formal child

[15]The child care subsidies and income transfers end at age 5 in my simulations. However, the effects of these programs can be traced through ages 10 to 11 (the terminal period of the model) because of the dynamic nature of the model.

care, which is estimated to have positive productivity in cognitive skill development and negative productivity in non-cognitive skill development.

Moreover, the results indicate that child care subsidies targeting lower income families are more cost-effective for improving child cognitive skill development. When targeting households with family income lower than 2,500 AUD per week,[16] government spending is 38.3% smaller than the universal child care subsidy, but the average cognitive skill at ages 10 to 11 is only 8.1% smaller. This is because in the absence of the subsidy, lower income families are less likely to use formal child care than are higher income families, but increase use of formal child care due to the subsidy by more from a lower base. These results suggest a rationale for targeted child care or preschool programs that serve disadvantaged children. The results are consistent with those from reduced form papers which find that the effects of universal programs are concentrated among disadvantaged children.[17]

The income transfer counterfactuals show that there are positive effects on both types of skills. In the no restriction scenario, a weekly 240 AUD universal income transfer, which is equivalent to the cost of 30 hours of formal child care per week, increases average cognitive and non-cognitive skills at ages 10 to 11 by 0.0092 and 0.0142 standard deviations, respectively, compared to the benchmark. The income transfer has small effects on time allocation; therefore, the positive effects on child skill development are due to an increase in monetary investment for skill development,[18] which is estimated to have positive productivity in both types of skill development. I also compare the effects of child care subsidy and income transfer programs, holding government spending constant. The results show

[16] In 2011–12, the average gross income per week was 2,580 AUD for a couple family with children (Australian Bureau of Statistics, 2013). The average exchange rate in 2012 was 1 AUD = 1.0356 USD.

[17] Baker (2011), Cascio (2015), Fitzpatrick (2008), Gormley and Gayer (2005), Havnes and Mogstad (2011b, 2015), Ruhm and Waldfogel (2012)

[18] In the model, households are assumed to invest a fixed proportion of net family income in children.

that the positive effect of the universal child care subsidy on cognitive skill is 247% greater than the positive effect of the universal income transfer.

One interesting result from the income transfer simulations is that the effects on children's skills are greater when maternal work is an eligibility requirement than when an income transfer is universal or income tested. When mothers must be employed to receive the transfer, the income transfer has a 32% to 45% greater effect on cognitive skill and 13% to 17% greater effect on non-cognitive skill than a universal income transfer or income transfer with income tests, holding government spending constant. This result can be explained as follows: A maternal work requirement encourages mothers to work, so family income and monetary investment in children increase, as does use of formal child care, which positively affects cognitive skill. Consequently, this result suggests that, when designing income transfer programs, providing mothers an incentive to work is important for improving child skill development.

I simulate the optimal program mix under alternative sets of assumptions about the relative weight placed by policy makers on cognitive and non-cognitive skills, assuming zero weight on parental utility per se.[19] The optimal program mix will depend on estimated parental preferences and skill production technologies as well as government goals. Policy makers choose a child care subsidy rate, and an transfer rate, whether to impose a maternal work requirement, and an income eligibility cutoff for each program. Using a 57% weight on cognitive skill and 43% on non-cognitive skill,[20] I find that the optimal program mix spends 6.9% of the budget on the child care subsidy and the rest on the income transfer. The

[19] I assume zero weight on parental utility since this study focuses on policies that are intended to improve child development.

[20] The weight is based on the result of Cunha et al. (2010). They find that 16% of the variation in educational attainment of young adults is explained by cognitive skill at ages 13 to 14 and 12% is explained by non-cognitive skill. Hence, 57% of the explained variation is due to cognitive skill.

optimal child care subsidy targets low income families, while the optimal income transfer serves low and middle income families and has a maternal work requirement. Since the child care subsidy has a negative effect on non-cognitive skill, it is optimal to spend only a small proportion of public funds on the child care subsidy and to target it to children who benefit the most in terms of improving cognitive skill. A large proportion of public funds is spent on the income transfer to offset the negative effect of the child care subsidy on non-cognitive skill and to boost cognitive skill for children in low income families since the income transfer has positive effects on both types of skills. The income transfer also improves the skills of children in middle income families. As a result, both types of skills are improved, with a larger increase in cognitive skill (0.0098 standard deviations) than in non-cognitive skill (0.0056 standard deviations).

The effect sizes described above are much smaller than those estimated by previous studies.[21] Several factors contribute to the small effect sizes. First, the programs considered here are for children aged 0 to 5, so the effects depreciate as children age after entering school.[22] Second, the effects of child care subsidies are mainly on the extensive margin, that is, mainly from households that are induced by the child care subsidy to use formal child care; these are 18.3% of all households under the no restriction scenario. Children in

[21] For example, Gormley and Gayer (2005) find that Oklahoma's universal pre-kindergarten increases cognitive skill measures by 0.24 to 0.39 standard deviations at ages 4 to 5. Baker et al. (2008) show that the effects of Québec's universal child care subsidy on non-cognitive skill measures at ages 0 to 3 are -0.09 to -0.12 standard deviations. For income effects, Dahl and Lochner (2012, 2017) find an increase in reading and math test scores at ages 5 to 14 by about 0.04 standard deviations for a 1,000 USD increase in family income. Milligan and Stabile (2011) find a 1,000 CAD increase in family income decreases mental and emotional problem measures at ages 4 to 10 by 0.07 to 0.10 standard deviations.

[22] The improvements in average cognitive and non-cognitive skills at ages 6 to 7 are 0.0249 and -0.0352 standard deviations for the 100% universal child care subsidy, respectively. These improvements are 0.0124 and 0.0362 standard deviations for the 240 AUD universal income transfer, respectively. These are more than twice as large as the improvements at ages 10 to 11. One exception is the effect of the income transfer on cognitive skill, where the effect at ages 6 to 7 is 34.8% greater than the effect at ages 10 to 11. The increase in non-cognitive skill due to the income transfers improves cognitive skill at school age because of the cross-productivity of non-cognitive skill at school age, so the effect of income transfers on cognitive skill depreciates slowly.

these families experience larger effects of child care subsidies,[23] but children in households that would have used formal child care in the absence of the subsidy experience smaller effects of the child care subsidy, because there is a smaller effect on the intensive margin. Hence, the average improvements in skills are small, as the majority of children experience small effects of child care subsidies on the intensive margin.[24] Third, parents allocate the income transfer mostly to their own consumption. Under the no restriction scenario, parents spend 85% of the income transfer benefit for their own consumption rather than for purchasing inputs to child skill production including formal child care.[25] This results in small effects of income transfers on child skill development. Lastly, the productivity of monetary investment may be smaller in early childhood than in adolescence. Del Boca et al. (2014) find a small productivity of monetary investment at younger ages, and show that the productivity of monetary investment increases as children age.[26] Thus, studies that analyze the effects of an income increase at older ages may find larger effects of income than my findings.[27,28]

[23] For example, the effects of the child care subsidy on cognitive and non-cognitive skills at ages 10 to 11 are 0.0360 and -0.0163 standard deviations, respectively, for children in households induced by the subsidy to use formal child care.

[24] One comparable study is Fitzpatrick (2008). She examines the effects of universal pre-kindergarten in the US state of Georgia, and finds small effects on cognitive skill measures at forth grade (increases of 0.008 to 0.027 standard deviations). One plausible reason that she mentions is a small shift on the extensive margin of pre-kindergarten participation.

[25] Del Boca, Flinn and Wiswall (2014) also find a small effect of income transfers on child cognitive skill, because parents use a large proportion of the additional income to have more leisure and consumption.

[26] They also simulate the effects of income transfers for ages up to 9 and income transfers for ages over 9, and find that the income transfer for younger ages has a much smaller effect.

[27] I also simulate the effects of income transfers for school age, and find that the average cognitive skill at ages 10 to 11 increases by 0.0512 standard deviations, which is comparable to the findings of Dahl and Lochner (2012, 2017) and Milligan and Stabile (2011). An increase in the average non-cognitive skill at ages 10 to 11 is 0.0166 standard deviations, which is smaller than the results of Milligan and Stabile (2011).

[28] Other factors that may contribute to the differences in the effect sizes include differences in skill measures, target population, and program features.

The rest of this chapter is organized as follows. Section 1.2 discusses how my analysis fits into the literature. Section 1.3 describes the model, and Section 1.4 presents the data and descriptive statistics. In Section 1.5, I discuss the estimation approach, while in Section 1.6, I present the estimates of the model and model fit. In Section 1.7, I discuss the results from my counterfactual policy experiments. Finally, Section 1.8 concludes this chapter.

1.2 Related Literature and Contributions of This Paper

This study is closely related to other papers that structurally estimate models of child care choice and child outcomes. While many of these studies analyze the effects of cash transfer programs only,[29] Bernal (2008) and Griffen (forthcoming) study how both child care subsidy and income transfer programs affect child cognitive skill development. Bernal (2008) simulates the effects of a 35% child care subsidy and a 250 USD quarterly baby bonus (or income transfer), but does not explicitly compare the effects of these two programs. Griffen (forthcoming) simulates the effect of removing Head Start and providing an income transfer of the same amount as per child spending for six-months of Head Start, but there is no channel for income to affect skill development in his model.

This study builds on the existing literature in several ways. First, my model incorporates both cognitive and non-cognitive skill production functions. Most previous studies consider only cognitive skill.[30] However, non-cognitive skill is a key determinant of educational attainment, employment, wages, and risky behaviors,[31] so ignoring non-cognitive skill may

[29] Del Boca et al. (2014), Del Boca, Flinn and Wiswall (2016), Mullins (2018)

[30] Mullins (2018) is the only paper to date in which the author structurally estimates a model with multiple skill measures (two cognitive measures and one non-cognitive measure), but he ignores non-parental child care, which is an important input for skill development.

[31] Cunha and Heckman (2007), Cunha et al. (2010), Heckman et al. (2006)

provide an incomplete analysis of public programs.[32] Indeed, Cunha et al. (2010) show evidence of the importance of considering both cognitive and non-cognitive skills.[33] Second, most previous papers do not consider all the inputs that my model includes.[34] That is, they exclude parental child care, non-parental child care, or monetary investment, or any two of the three inputs. However, all these inputs are important determinants of skill production in early childhood, and parental decisions on these inputs are influenced by child care subsidy and income transfer programs. Therefore, a missing input could result in understating or overstating the effects of public programs on child skill development. As mentioned above, there is no direct channel for income to affect child skill development in Griffen (forthcoming) because monetary investment is omitted from the skill production function. This missing channel could understate the effect of an income transfer on child skill development if monetary investment positively affects child skill development. Third, I allow two types of non-parental child care: formal and informal child care. Formal child care might provide more stimulating environments for child skill development than informal child care. Bernal (2008) assumes a homogeneous type of non-parental child care, which

[32]Some previous studies find that preschool and non-parental child care have positive effects on cognitive skill (e.g., Cascio and Schanzenbach, 2013, Fitzpatrick, 2008, Gormley and Gayer, 2005, Magnuson, Ruhm and Waldfogel, 2007), while other studies show a negative effect on non-cognitive skill (Baker et al., 2008, Baker, Gruber and Milligan, forthcoming, Magnuson et al., 2007, e.g.,). Hence, if child care subsidies promote use of preschool or non-parental child care, then ignoring non-cognitive skill could result in different policy implications.

[33]One important implication of their study is that investment is most productive if it is targeted to disadvantaged children at younger ages. However, when they ignore non-cognitive skill and considering only cognitive skill, they find that investment in advantaged children at younger ages is more productive.

[34]Del Boca et al. (2014, 2016) and Mullins (2018) do not use non-parental child care as an input, probably because they do not focus on early childhood and analyze the effects of cash transfer programs only. Chan and Liu (forthcoming) is the only paper in which the authors consider all inputs, but their cognitive skill production function is not jointly estimated with their model of child care. This implies that parents do not care about the skill development of children when making decisions. They examine the "cash-for-care" program in Norway, which is an income transfer that is given to families with young children who do not use subsidized formal child care. They find that the "cash-for-care" program decreases the cognitive skill of children of low-education mothers. This is driven by more use of informal child care and less use of formal child care. However, the effects may be overstated because if mothers care about children and if informal child care has a lower quality than formal child care, then the changes in use of formal and informal child care could be smaller, and so could be the effect on children.

could result in an understated effect on child skill development of a policy that promotes use of non-parental child care if informal child care has an adverse effect on cognitive skill development.[35]

This study is also related to the literature on the effect of intervention programs that target disadvantaged children,[36] such as Abecedarian, Perry Preschool and Head Start,[37,38] and universal preschool programs in Europe, South America, and the US.[39] Similar to my findings, these papers consistently show a positive effect of such programs on measures of cognitive skill.[40] Some papers examine the effects of the programs on non-cognitive skill development of children, but find a positive effect on non-cognitive skill, in contrast with my results.[41] However, Baker et al. (2008, forthcoming) who examine the effects of Québec's universal child care program in Canada find a negative effect on non-cognitive skill outcomes, which is consistent with the results of my study. However, Baker et al. (forthcoming) also show that the Canadian program decreases cognitive skill test scores.[42]

[35]Bernal (2008) assumes a homogeneous type of non-parental child care, which conflates formal and informal child care, and finds that the child care subsidy has a negative effect on child cognitive skill. Bernal and Keane (2011) and Chapter 2 of this dissertation show that informal child care has a negative effect on child cognitive skill. Hence, the negative effect could be because of informal child care.

[36]For an extensive reviewof this literature, see Baker (2011), Baker et al. (2008, forthcoming), Cascio (2015), Herbst and Tekin (2010), Kautz, Heckman, Diris, ter Weel and Borghans (2014).

[37]Carneiro and Ginja (2014), Cunha, Heckman, Lochner and Masterov (2006), Deming (2009), Heckman, Pinto and Savelyev (2013), Heckman, Moon, Pinto, Savelyev and Yavitz (2010), Ludwig and Miller (2007)

[38]Early intervention programs can be thought of as a child care subsidy targeting disadvantaged children.

[39]Cascio (2015), Fitzpatrick (2008), Gormley and Gayer (2005), Havnes and Mogstad (2011b, 2015), Ruhm and Waldfogel (2012)

[40]For example, Deming (2009) shows that Head Start participation increases cognitive test scores by 0.145 standard deviations at ages 5 to 6 and by 0.055 standard deviations at ages 11 to 14. The effect at ages 11 to 14 is imprecisely estimated. Havnes and Mogstad (2011b) find that Norwegian universal child care subsidy increases years of schooling per child by 0.06 years. See also footnotes 21 and 24.

[41]For example, Carneiro and Ginja (2014) find sizable decreases in behavioral problems at ages 12 to 13 and depression at ages 16 to 17. Heckman et al. (2013) show that Perry Preschool improves non-cognitive skill measures at ages 7 to 9.

[42]For example, according to Baker et al. (forthcoming), the universal child care increases anxiety and aggression at ages 2 to 3 by 0.115 and 0.117 standard deviations, respectively, and decreases the Peabody Picture Vocabulary Test score at ages 4 to 5 by 0.109 standard deviations.

Another stream of literature related to this study estimates the effect of income on child skill development.[43] Recent papers in this literature use exogenous policy variations, such as the Earned Income Tax Credit in the US, child tax benefits in Canada, and cash disbursements of a newly opened casino to American Indians in rural North Carolina, to identify the effects of income on children.[44] The results of these papers consistently indicate that additional family income at school age has a positive effect on measures of cognitive and non-cognitive skills,[45] which is similar to my findings.

1.3 Model

In this section, I develop a discrete-time, dynamic model of two-parent households' decisions about labor supply and child care. The model begins when a child's age is 0 to 1 years ($t = 1$), and ends when the child's age is 8 to 9 years ($t = 5$). The length of the decision period is two years. In each period t, a household makes decisions about hours of maternal work ($h_{m,t}$), hours of paternal child care ($\tau_{f,t}$), hours of formal non-parental child care ($\tau_{fc,t}$), and hours of informal non-parental child care ($\tau_{ic,t}$).[46] I assume that fertility follows an exogenous stochastic process. Only one child in a household is analyzed, and

[43] For a detailed review of the literature on the effect of income on children, see Dahl and Lochner (2012), Duncan and Brooks-Gunn (1997), Haveman and Wolfe (1995), Heckman and Mosso (2014), Mayer (1997), and Milligan and Stabile (2011).

[44] Dahl and Lochner (2012, 2017), Milligan and Stabile (2011), Akee et al. (2010, 2018)

[45] Milligan and Stabile (2011) show that a 1,000 CAD increase in family income raises vocabulary and math test scores at ages 4 to 10 by 0.02 to 0.04 standard deviations. Akee et al. (2010) show that additional income from transfers increases educational attainment for children in low income families by a year and the probability of high school graduation by 39%. Akee et al. (2018) examine the effects of household income on various measures of personality traits and behaviors during adolescence, and find that receiving cash transfers has positive effects of 0.21 to 0.37 standard deviations. See also footnote 24.

[46] Hours of maternal child care $\tau_{m,t}$ and hours of maternal leisure $l_{m,t}$ are residuals from the time constraints, which will be explained below.

there is no resource allocation among multiple children.[47] Parents also make no decision on marriage and divorce. Lastly, there is no saving or borrowing.

1.3.1 Utility Function and Constraints

The current-period utility function is given by

$$u_t = u_t(x_t, h_{m,t}, \tau_{f,t}, \tau_{fc,t}, \tau_{ic,t}, \theta_{c,t}, \theta_{n,t}; \boldsymbol{X}_t^u, type, \boldsymbol{\varepsilon}_t). \tag{1.1}$$

The current-period utility of a household depends on consumption (x_t), hours of maternal work, hours of paternal child care, hours of formal child care, hours of informal child care, and the child's current cognitive and non-cognitive skill levels ($\theta_{c,t}$ and $\theta_{n,t}$, respectively).[48] The vector $\boldsymbol{X}_t^u$ includes observed variables such as parental education and the number of children, which shift parents' tastes for maternal work, paternal child care, and informal child care. I allow preferences to vary with child's age. The variable *type* captures permanent unobserved preference heterogeneity. The vector $\boldsymbol{\varepsilon}_t$ is a vector of serially independent preference shocks, which are assumed to be jointly normally distributed. The exact form of the utility function is provided in Appendix A.1.

[47] The number of children affects parents' preferences, as discussed below. Del Boca et al. (2014) consider households with up to two children in their study about household time allocation and child cognitive development.

[48] The utility function depends on maternal hours of work, not leisure. I use this approach because it makes the model more tractable.

The budget constraint faced by the household is given by

$$\begin{aligned}
&x_t + g_t + p_{fc}\tau_{fc,t} + p_{ic}\tau_{ic,t} + TAX_t(h_{m,t}, w_{m,t}, e_{f,t}) \\
&\quad = w_{m,t}h_{m,t} + e_{f,t} \\
&\qquad + CCB_t(p_{fc}, p_{ic}, \tau_{fc,t}, \tau_{ic,t}, h_{m,t}, w_{m,t}, e_{f,t}, t) \\
&\qquad + CCR_t(p_{fc}, \tau_{fc,t}, h_{m,t}, CCB_t) \\
&\qquad + FTB_t(h_{m,t}, w_{m,t}, e_{f,t}, yage_t, N_t) \\
&\qquad + PP_t(h_{m,t}, w_{m,t}, e_{f,t}),
\end{aligned} \tag{1.2}$$

where g_t is expenditure on the child other than child care; p_{fc} and p_{ic} are prices per hour of formal and informal non-parental child care, respectively; $w_{m,t}$ is mother's hourly wage; and $e_{f,t}$ is father's weekly earnings. Fathers are assumed to work full time. It is assumed that expenditure on the child is a fixed proportion (π) of family income net of tax and income transfers, as follows:[49]

$$\begin{aligned}
g_t = \pi\Big\{ & w_{m,t}h_{m,t} + e_{f,t} - TAX_t(h_{m,t}, w_{m,t}, e_{f,t}) \\
& + FTB_t(h_{m,t}, w_{m,t}, e_{f,t}, yage_t, N_t) + PP_t(h_{m,t}, w_{m,t}, e_{f,t})\Big\}.
\end{aligned} \tag{1.3}$$

In the equation above, $TAX_t(h_{m,t}, w_{m,t}, e_{f,t})$ is an income tax function. If eligible, the household receives child care subsidies, income transfers, or both. $CCB_t(p_{fc}, p_{ic}, \tau_{fc,t}, \tau_{ic,t}, h_{m,t}, w_{m,t}, e_{f,t}, t)$ is the Child Care Benefit (CCB) function. Both formal and informal child care are eligible for CCB, but the rate is smaller for informal child care. CCB is income tested, and the rate depends on hours of child care, hours of maternal work, and whether the child is school aged. $CCR_t(p_{fc}, \tau_{fc,t}, h_{m,t}, CCB_t)$ is the Child Care Rebate (CCR) function.

[49] This assumption is due to lack of data on expenditure on children and computational infeasibility. It is ideal to consider expenditure on the child as a choice, but then solving and estimating the model would require extremely longer computation time.

Only formal child care is eligible for CCR. It is not income tested, but maternal work is required for the household to receive CCR. CCR pays a portion of out-of-pocket expenses for formal child care up to a maximum limit. $FTB_t(h_{m,t}, w_{m,t}, e_{f,t}, yage_t, N_t)$ is the Family Tax Benefit (FTB) function. FTB is income tested, but it has no work requirement. Finally, $PP_t(h_{m,t}, w_{m,t}, e_{f,t})$ is the Parenting Payment (PP) function. PP is income tested, and it has a maternal work requirement. Parents make decisions on labor supply and child care conditional on the eligibility restrictions of these child care subsidies and income transfers, so the model captures how families respond to changes in these programs. Further details about these policy functions can be found in Appendix A.2.

The time constraints of household members are given by

$$\text{Mother: } h_{m,t} + \tau_{m,t} + l_{m,t} = T^p \tag{1.4}$$

$$\text{Father: } h_{f,t} + \tau_{f,t} + l_{f,t} = T^p \tag{1.5}$$

$$\text{Child: } \tau_{m,t} + \tau_{f,t} + \tau_{fc,t} + \tau_{ic,t} = T^{chd} - 30I(t = 4, 5), \tag{1.6}$$

where T^p and T^{chd} are total available time for parents and child, respectively;[50] $\tau_{m,t}$ is hours of maternal child care; and $l_{m,t}$ and $l_{f,t}$ are the number of maternal and paternal leisure hours, respectively. Maternal child care time, $\tau_{m,t}$, is a residual from the child time constraint. As mentioned earlier, I assume that fathers always work full-time ($h_{f,t} = 40$).[51]

[50] I assume that $T^p = 112$ and $T^{chd} = 90$. More details about how to set total available time for children are in Section 1.4.

[51] Only a small proportion of all fathers in the sample are non-workers or part-time workers. Specifically, about 4% to 6% of children in the sample live with fathers who work less than 20 hours per week (including zero) in each period.

Maternal and paternal leisures are a residual from mother and father time constraints, respectively. School age children are assumed to attend school 30 hours per week.[52]

1.3.2 Technology of Skill Formation

The initial levels of a child's cognitive and non-cognitive skills are determined by the child's characteristics, such as sex, birth weight (bw) and whether the birth is premature (pb); mother's characteristics, such as education ($educ_m$), employment during pregnancy ($emppreg$), and age at birth of child;[53] and $type$ of household. Specifically, the initial skills are given by

$$\theta_{r,1} = f_0^r(sex, bw, pb, age_{m,1}, educ_m, emppreg; type, \eta_{r,1}), \quad r \in \{c, n\}, \tag{1.7}$$

where the subscript of $f(\cdot)$ indicates the initial stage, and $\eta_{r,1}$ is a productivity shock.

Technology is allowed to vary with stage of child development. I assume that there are two stages: before schooling ($s = 1$: $t = 1, 2, 3$) and primary schooling periods ($s = 2$: $t = 4, 5$), and all parameters are allowed to differ by stage. In the first stage, skill production is a function of the current levels of cognitive and non-cognitive skills, paternal child care time, formal and informal non-parental child care time, expenditure on the child, and type of household:

$$\theta_{r,t+1} = f_1^r(\theta_{c,t}, \theta_{n,t}, \tau_{f,t}, \tau_{fc,t}, \tau_{ic,t}, g_t; type, \eta_{r,t+1}), \quad r \in \{c, n\}, \tag{1.8}$$

where the subscript of $f(\cdot)$ indicates stage 1 (before-schooling); $\eta_{r,t+1}$ is a productivity shock, which is observed by parents at the beginning of the next period, after choices have

[52] In Australia, the usual school hours are 9 a.m. to 3 p.m., and children attend school from Monday to Friday.

[53] The characteristics of child and mother are assumed to be exogenous.

been made at period t. In the second stage, the child enters primary school, so the quality of the school that the child attends (q_t) is added as an input. The production function is given by

$$\theta_{r,t+1} = f_2^r(\theta_{c,t}, \theta_{n,t}, \tau_{f,t}, \tau_{fc,t}, \tau_{ic,t}, g_t, q_t; type, \eta_{r,t+1}), \quad r \in \{c, n\}, \tag{1.9}$$

where the subscript of $f(\cdot)$ indicates stage 2 (primary schooling). Note that the production functions incorporate dynamic features of skill formation that have been established as important in the recent literature: self-productivities of cognitive and non-cognitive skills (i.e., $\frac{\partial \theta_{c,t+1}}{\partial \theta_{c,t}} \neq 0$ and $\frac{\partial \theta_{n,t+1}}{\partial \theta_{n,t}} \neq 0$) and cross-productivity between cognitive and non-cognitive skill (i.e., $\frac{\partial \theta_{c,t+1}}{\partial \theta_{n,t}} \neq 0$ and $\frac{\partial \theta_{n,t+1}}{\partial \theta_{c,t}} \neq 0$). The exact form of the skill production functions is given in Appendix A.1.

There are several things to note about the functional forms of the skill production functions. First, in empirical analysis, the skill production functions are assumed to be linear in the current levels of skills and quadratic in other inputs (hours of paternal child care, hours of formal and informal child care, expenditure on the child, and school quality). A key advantage of this functional form is that the production function allows for zero input levels. This is important because many households do not use non-parental child care, that is, $\tau_{fc,t}$ and $\tau_{ic,t}$ could have zero values. One drawback is a large number of parameters, which would lead to computationally burdensome estimation. [54] Second, maternal child care is excluded because of perfect multicollinearity in linear terms on time inputs. As specified in (1.6), the sum of maternal, paternal, formal, and informal child care time is

[54] An alternative functional form is a constant elasticity of substitution (CES). CES has fewer parameters than the functional form used here, but it does not allow zero levels of inputs. Since many households do not use non-parental child care, the CES is an inappropriate specification here. Cunha et al. (2010) use a CES production function and consider only a single investment, which is measured based on many measurements of the child's home environment.

a constant (i.e., total available time for child), so including all types of child care time inputs leads to perfect multicollinearity. Since maternal child care is excluded, I identify the marginal productivity of each time input relative to maternal child care.[55] Lastly, the quality of each type of child care is homogeneous. Thus, the productivity parameters identify the productivity of the average quality of each type of care.

1.3.3 Maternal Wage, Paternal Earnings, Fertility, and School Quality

The maternal wage and paternal earnings similarly follow the standard Mincer wage and earnings functions. The log weekly maternal wage depends on the mother's age, education, and work experience ($expr_t$); and household type:

$$lnw_{m,t} = f^m(age_{m,t}, educ_m, expr_t; type, \varepsilon_{m,t}), \tag{1.10}$$

where $\varepsilon_{m,t}$ is a serially independent and normally distributed random shock to the mother's productivity.[56] The log weekly paternal earnings depend on the father's age and education, and household type:

$$lne_{f,t} = f^f(age_{f,t}, educ_f; type, \varepsilon_{f,t}), \tag{1.11}$$

where $\varepsilon_{f,t}$ is a serially independent and normally distributed random shock. Fertility follows a stochastic process, which depends on the mother's age and education, the current number

[55] Consider a very simple linear production function with maternal and non-maternal child care, as follows: $\theta = \gamma_0 + \gamma_1\tau_m + \gamma_2\tau_{nm} + \varepsilon$, where θ is child's skill, τ_m is maternal child care, and τ_{nm} is non-maternal child care. Assuming that a child's total available time is the sum of maternal child care time and non-maternal child care time, the time constraint is $T = \tau_m + \tau_{nm}$. In this setting, there is perfect multicollinearity since maternal child care and non-maternal child care have a linear relation. From the time constraint, we have $\tau_m = T - \tau_{nm}$. Substituting this for τ_m in the linear production function yields $\theta = \hat{\gamma}_0 + \hat{\gamma}_1\tau_{nm} + \varepsilon$, where $\hat{\gamma}_0 = \gamma_0 + \gamma_1 T$ and $\hat{\gamma}_1 = \gamma_2 - \gamma_1$. $\hat{\gamma}_1$ is the marginal productivity of non-maternal child care relative to maternal child care.

[56] The coefficient on $age_{m,t}$ captures the depreciation of maternal wage offer for an additional year of unemployment. Conditional on maternal education and work experience, an extra year of age implies an additional year of unemployment.

of children, and the ages of the youngest and oldest child:

$$N_{t+1} = N_t + I(\varepsilon_{b,t} < Pr(N_{t+1} = N_t + 1; age_{m,t}, educ_m, N_t, yage_t, oage_t, type)), \quad (1.12)$$

where $\varepsilon_{b,t}$ follows a uniform distribution, $U(0,1)$. The quality of school that the child attends is assumed to be a function of parental education and the household type:

$$q_t = f^q(educ_m, educ_f; type, \varepsilon_{q,t}) \quad (1.13)$$

Appendix A.2 shows the exact forms of the above functions.

1.3.4 Dynamic Problem

A household optimally chooses the maternal hours of work, hours of paternal child care, and hours of non-parental formal and informal child care to maximize the expected present discounted value of utility at each period $t = 1, \cdots, 5$.[57] The value function of the household at t is given by

$$V_t(\Omega_t) = \max_{h_{m,t}, \tau_{f,t}, \tau_{fc,t}, \tau_{ic,t}} \{u_t + \beta E_t V_{t+1}(\Omega_{t+1})\}, \quad (1.14)$$

where β is the discount factor, and E_t is the expectation operator conditional on the period t information set. The conditional expectation is taken over the distribution of future shocks to preferences, skill development, maternal wage, paternal earnings, school quality, and fertility. The vector of state variables Ω_t includes endogenously determined state variables such as current levels of the child's skills and maternal work experience; exogenously determined state variables such as parents' age and education, the number of children,

[57]Note that maternal child care is determined by choices of other types of child care since it is a residual from the child time constraint.

and the ages of youngest and oldest child; the household type; and the realization of the current-period shocks.

Instead of modeling the household's behavior after the last period of the model ($t = 5$), for which no data are available, I assume that there exists a terminal value that depends on the predicted levels of child's skills and state variables at $t = 6$, and decisions made at $t = 5$. These "terminal" levels of the child's skills can be considered as the initial condition for the next stage of child development. The terminal value function is given by

$$V_6(\Omega_6) = \kappa_1 \log \frac{\hat{x}}{1000} - \kappa_2 \exp(-\bar{\theta}_{c,6}) - \kappa_3 \exp(-\bar{\theta}_{n,6}), \tag{1.15}$$

where $\hat{x}$ is predicted consumption, which depends on the state variables at $t = 6$ and decisions made at $t = 5$,[58] and $\bar{\theta}_{c,6}$ and $\bar{\theta}_{n,6}$ are the predicted cognitive and non-cognitive skill levels, respectively. The terminal value reflects how parents value the remaining lifetime utility from their child's skills and consumption. The terminal value function has a different functional form from the utility function to separately identify the parameters in the terminal value function from those in the utility function.

1.3.5 Solution

In practice, it is very challenging or infeasible to solve the model with many continuous choice variables. This is because there are many kinks in the budget constraint due to child care subsidy and income transfer policies, so there are many corner solutions to evaluate.

[58] Similar to Bernal (2008), $\hat{x}$ is predicted as:

$$\hat{x} = \bar{w}_{m,6} E(h_{m,6}) + \bar{e}_{f,6},$$

where $\bar{w}_{m,6}$ is the predicted wage of the mother given the state variables at $t = 6$, and $E(h_{m,6})$ is the expected hours of maternal work given the state variables at $t = 6$ and decisions made at $t = 5$. Similarly, $\bar{e}_{f,6}$ is the predicted earnings of the father given the state variables at $t = 6$.

For this reason, I discretize the choice variables (hours per week) as follows:[59]

$$\begin{aligned}
\text{Maternal Work: } & h_{m,t} \in \{0, 8, 20, 30, 40\} \\
\text{Paternal Child Care: } & \tau_{f,t} \in \{0, 3, 7, 12, 26\} \\
\text{Formal and Informal Child Care: } & \tau_{fc,t}, \tau_{ic,t} \in \{0, 6, 14, 24, 38\} \\
& \quad \text{for } t = 1, 2, 3 \text{ (Preschool)} \\
& \tau_{fc,t}, \tau_{ic,t} \in \{0, 3, 7, 12, 20\} \\
& \quad \text{for } t = 4, 5 \text{ (School)}
\end{aligned} \tag{1.16}$$

The values of formal and informal child care for school age are different from those for preschool age because children generally spend a small number of hours in formal and informal child care before and after school. The set of discrete choices is $\{(h_{m,t}, \tau_{f,t}, \tau_{fc,t}, \tau_{ic,t})\}$.[60]

The model is numerically solved by backward recursion, beginning with the assumed terminal value function. To solve the model numerically, I need to evaluate the value function at every point of the state space; however, this is infeasible since the size of the state space is large and children's skills are continuous. I adopt an approximation approach developed by Keane and Wolpin (1994). The solution of the model can be considered as the set of values of "Emax" functions: $E_t[V_{t+1}(\Omega_{t+1})|k, \Omega_t]$ for all t, alternative k and points of Ω_t. The Emax functions are evaluated at a subset of the state space, and then a regression of the Emax functions on a polynomial of the state variables is estimated. Using the estimates

[59]The discrete values of choice variables are chosen, as follows: First, zero is one discrete point since there are many zero values. For values greater than zero, four mutually exclusive intervals are chosen based on the distributions of choice variables. After that, an integer number close to the mean for each interval is chosen for a discrete point. For more details and the distributions of choice variables, see Appendix A.3.

[60]Some combinations of the time allocation variables are not in the choice set, because they do not satisfy the time constraints. For example, $(h_{m,t}, \tau_{f,t}, \tau_{fc,t}, \tau_{ic,t}) = (40, 0, 0, 0)$ is not in the choice set, because maternal leisure is negative, and $(h_{m,t}, \tau_{f,t}, \tau_{fc,t}, \tau_{ic,t}) = (0, 26, 38, 38)$ is not in the choice set, because maternal child care is negative.

of the regression, I can interpolate or extrapolate the values of the Emax functions at other points of the state space.

There were some changes in child care subsidies and income transfers during the period of analysis. I assume that parents do not anticipate these changes, and solve the dynamic problem for each policy regime. Specifically, before a change in a policy, households make decisions under the assumption that the policy stays fixed in the future. After the policy changes, households make decisions under the assumption that the changed policy stays fixed in the future. Hence, the value function has to be evaluated for each observed policy regime.

1.3.6 Measurement Equations

Instead of actual levels of cognitive skill, non-cognitive skill, and school quality, which I do not observe, I use summary indexes.[61] The summary indexes proxy the true levels of skills and school quality with some error. Let $m_{c,t}$, $m_{n,t}$, and $m_{q,t}$ be a summary index at period t for cognitive skill, non-cognitive skill, and school quality, respectively. The measurement equations can be written as follows:

$$m_{c,t} = \theta_{c,t} + \nu_{c,t} \tag{1.17}$$

$$m_{n,t} = \theta_{n,t} + \nu_{n,t} \tag{1.18}$$

$$m_{q,t} = q_t + \nu_{q,t}, \tag{1.19}$$

[61]See Section 1.4 for details about how to construct the indexes. See also Anderson (2008) for further details and a discussion of identification.

where $\nu_{k,t}$, for $k \in \{c, n, q\}$, is a measurement error, which is serially independent and normally distributed. The measurement equations are estimated jointly with the model.[62]

1.4 Data

The model is estimated using data from the Longitudinal Study of Australian Children (LSAC). The LSAC surveyed two cohorts every two years from 2004. The first cohort of 5,107 children was born between March 2003 and February 2004 (aged 0 to 1 years in 2004), and the second cohort of 4,983 children was born between March 1999 and February 2000 (aged 4 to 5 in 2004). Since the model of this study covers periods from birth, the first cohort is used. The LSAC collected very rich information about children's cognitive and non-cognitive skills. For each survey year, there are 6 to 16 measures for cognitive skill, and 7 to 29 measures for non-cognitive skill. The LSAC collected information about up to three child care arrangements that parents used for the first three survey years, including the type of arrangement and hours per week for each arrangement used. After children began primary schooling, the same information is available for before- and after-school child care and child care for evenings and weekends. The LSAC also collected the number of hours that a child is regularly cared for by the father or mother's partner only. In addition, the LSAC contains information about schools that children attend, including enrollment, the number of teaching staff, budget, capital expenditure, and average scores of the National Assessment Program - Literacy and Numeracy. The LSAC also contains information on the children, such as sex, age, birth weight, and gestation length; information on parents, such

[62]This approach is similar to Bernal (2008). She estimates a structural model jointly with a measurement equation for cognitive skill, using reading and math test scores, but she does not use a summary index. I do not use a factor model because there are too many parameters to be estimated due to many measures for skills and school quality, so it is infeasible to jointly estimate a factor model with a structural model.

as age, education, average hours worked per week, and usual weekly income; and family characteristics, such as the number of children and ages of the youngest and oldest child.

The sample used in the analysis includes children who live with two parents in the same household. I analyze outcomes of only one child in the households because detailed data are collected for only one child per household. I focus on married or cohabiting couples because information on a parent who does not live with the child is missing for a large number of children in the data.[63,64] Children who attended school in the third survey year (or when they were 4 to 5 years old) are excluded since age 0 to 5 is preschool stage in the model.[65] After excluding observations with missing values for initial conditions and hours of child care and work, there are 2,102 children in the estimation sample.

Total available time for children is defined as the hours that children are awake. The LSAC collected Time Use Diaries for the first three survey years, and asked respondents about the usual time that the child goes to bed and wakes up for the next three survey years. I use this information to obtain the average sleeping hours and average waking hours per week.[66]

Table 1.1 shows descriptive statistics of hours of maternal work and child care. As expected, the employment rate of mothers increased as their child aged. The maternal

[63] Compared to the US, Australia has a relatively smaller fraction of children who live with one parent only. In 2012–13, the fraction of children with one parent in the same household was 16.5% in Australia. In 2014, the fraction was 27.2% in the US. (Source: OECD Family Database)

[64] To account for marriage and divorce, information on a parent who does not live with the child is required in the case of divorce. Unfortunately, the information was not collected at the child's ages 0 to 1, and there is a large number of missing observations at the child's ages 2 to 3.

[65] There are 388 such children.

[66] The calculated average waking hours are 73.7 hours at age 0 to 1, 87.3 hours at age 2 to 3, 92.3 hours at age 4 to 5, 91.5 hours at age 6 to 7, and 93.6 hours at age 8 to 9. The calculated average waking hours is small at age 0 to 1 because children sleep much at this age. However, they should be cared for by someone even when they sleep, especially at this age, so child care demand would be larger than the average waking hours. Based on this fact and the computed average waking hours above, total available time for children is set to 90 hours per week in each period.

	Ages	Maternal Employment (1)	Paternal Child Care (2)	Formal Child Care (3)	Informal Child Care (4)
% Non-Zeros	0 to 1	40.8%	42.5%	14.2%	25.3%
	2 to 3	56.3%	45.3%	52.5%	31.6%
	4 to 5	64.3%	48.5%	95.8%	30.6%
	6 to 7	70.8%	51.7%	18.1%	23.5%
	8 to 9	76.4%	53.3%	14.5%	23.5%
Mean $\mid > 0$	0 to 1	17.0	7.2	18.2	12.3
	2 to 3	20.1	7.8	17.2	12.0
	4 to 5	21.0	8.2	17.4	10.2
	6 to 7	22.8	6.8	5.1	6.4
	8 to 9	25.1	6.8	5.6	6.4

Note: % Non-Zero is the fraction of non-zero values. Means are calculated for non-zero values. Non-parental formal care is child care that meets certain standards and requirements enforced by the government, such as long day care and family day care. Non-parental informal care is all other types of care, such as care by relatives or non-relatives. The values in this table are based on continuous data, not on discretized data.

Table 1.1: Hours of Maternal Work and Child Care

employment rate was 40.8% when the children were 0 to 1 years old, and it increased to 76.4% when the children were aged 8 to 9. The average hours of maternal work increased from 17 hours per week when the children were 0 to 1 year old to about 25 hours per week when the children were aged 8 to 9. The fraction of children who spent any time in paternal care increased from 42.5% at age 0 to 1 to 53.3% at age 8 to 9. The average hours of paternal child care was 7.2 to 8.2 hours per week during preschool age, and slightly decreased to 6.8 hours per week during school age. Use of non-parental formal child care significantly increased during preschool periods. Only 14.2% of children were in non-parental formal childcare when they were aged 0 to 1, but the proportion increased to 52.5% at age 2 to 3, and reached 95.8% at age 4 to 5.[67] More children experienced non-parental informal child care than formal child care at age 0 to 1, but use of informal child care increased only

[67] The large fraction at age 4 to 5 could be because of a large increase in child care subsidy benefit at these ages and the inclusion of preschool programs as formal child care.

slightly, from 25.3% to around 30.6%, during preschool periods. When formal child care was used during preschool age, children spent about 17.2 to 18.2 hours per week on average in formal child care. The average hours of informal child care use was smaller, at around 10.2 to 12.3 hours per week. Informal child care was used more than formal child care at school age. In total, 23.5% of school age children experienced informal child care, while 14.5% to 18.1% experienced formal child care. As expected, school aged children spent a small amount of time (5.1 to 6.4 hours) in non-parental child care.

For measures for cognitive and non-cognitive skills, I construct a summary index of each skill type for each period, using measures listed in Appendix A.5. For example, the measures of cognitive skill include parents' concerns about child's development, speech, and motor skills; language development scales based on use of vocabulary and grammar; test scores such as the "Who am I?" assessment, the Peabody Picture Vocabulary Test, and the Matrix Reasoning test; and reading and math progress evaluated by mothers and teachers. The measures of non-cognitive skill include degrees of positive and negative response, fear, and shyness to a survey interviewer; ratings of persistence, reactivity, sociability, and self-perception; social emotional problem ratings by mothers, teachers, and children themselves, such as hyperactivity scale, emotional scale, and peer problems scale in the Strengths and Difficulties Questionnaire. The measures are adjusted, if necessary, so that higher values indicate better outcomes. The summary index is a weighted average of standardized measures, and the weight is the sum of its corresponding row in the inverse of the variance covariance matrix of the standardized measures. This ensures that more weight is assigned if a correlation between two measures is smaller, meaning that more weight is placed on new information.[68] The summary indexes are then restandardized for each period.

[68]See Anderson (2008) for more details.

1.5 Estimation Approach and Identification

As described in Section 1.3.5, the size of the choice set is large. Evaluation of probabilities for such a large number of choices, each of which is an element of the likelihood function, is computationally burdensome. Moreover, there are missing observations on some variables.[69] Thus, I use a simulation-based method, indirect inference, to estimate the model parameters.[70] Indirect inference uses auxiliary descriptive statistical models that are easy to estimate. Specifically, I first estimate the parameters of the auxiliary models by maximum likelihood using actual data. The parameter values of the structural model are then chosen to minimize an objective function that is a weighted sum of the squared score functions for the likelihood functions of the auxiliary models. The score functions are evaluated at simulated data, with respect to the maximum likelihood estimates of the auxiliary models. At the maximum likelihood estimates of the auxiliary models, the score functions of the likelihood must be zero with respect to the actual data. Thus, the idea is to choose the structural model parameters that make the score functions evaluated at simulated data as close to zero as possible. The estimation process iterates between solving the model and computing the objective function. Given candidate model parameters, I solve the model by backward recursion, and then generate simulated data, which I use evaluate the objective function. This procedure iterates until the objective function is minimized.

The first set of auxiliary models consists of multinomial logits for hours of maternal work, paternal child care and non-parental formal and informal child care. The specifications of these auxiliary models include state variables such as parents' age and education, maternal work experience, the number of children, ages of the youngest and oldest child, and the

[69] In the first two waves of the survey, parents' wages were not collected separately from total income including non-labor income. Skill measures are also missing for some children.

[70] Gourieroux, Monfort and Renault (1993), Smith (1993), Gallant and Tauchen (1996)

current levels of the child's skills. The motivation for these model specifications is that the solution to the model described in Section 1.3 is a set of outcome functions of all the state variables.[71] Thus, the auxiliary models are parametric approximations to the outcome functions. Following van der Klaauw and Wolpin (2005, 2008), I use a subset of the state variables in the auxiliary models to obtain parsimonious representations and reasonable precision in the parameter estimates.

The first set of the auxiliary models will help to identify preference parameters by capturing the relationship between choices made by parents and observed variables. For example, the intercept and coefficients on the observed variables in the multinomial logit for hours of maternal work will help to identify disutility from maternal work and heterogeneity in preference by the observed variables. The specifications of the auxiliary models also include the current levels of children's skills. This will help to identify preference parameters for the skills. To identify differences in utility function parameters by age, age dummies are included in some of the auxiliary models.

The second set of auxiliary models is a set of regressions of next-period skills, initial skills, log (accepted) maternal wages, log paternal earnings, and school quality; and a logit for having a newborn child. These auxiliary models have similar specifications to those of the behavioral model. Since the child's skills and school quality are unobserved, I use summary indexes of the skills and school quality, instead of true values. I also cannot

[71] As described in van der Klaauw and Wolpin (2005, 2008), the decision rules obtained from the model should be functions of all the state variables of the following form:

$$d_t^k = \begin{cases} 1 & \text{if } V_t^k(\Omega_t^k) - V_t^{-k}(\Omega_t^{-k}) = F_t^k(\Omega_t) > 0 \\ 0 & \text{otherwise} \end{cases}, \tag{1.20}$$

where Ω_t^k includes state variables that are relevant to alternative k and $V_t^{-k}(\Omega_t^{-k})$ is the maximum of the alternative-specific value functions for alternatives except k. As shown in (1.20), the decision rules depend on all state variables (Ω_t), given a chosen function F.

observe expenditures on the child, so family income is included in the corresponding regressions. Each specification includes the same variables as in the model in Section 1.3, so the model parameters will be identified by the corresponding coefficients in the auxiliary models. To allow the identification of the unobserved permanent heterogeneity parameters, each specification includes additional variables which are not determinants of the outcome of the specification. For example, the auxiliary models of initial skills include maternal work experience, and the auxiliary model of the wage offer process includes the number of children and ages of the youngest and oldest child.

There is no natural experiment with a comparison group to use as an exogenous source of identification.[72] However, there is some exogenous variation that is used to help identify the model. The Australian child care subsidies and income transfers are highly nonlinear in nature, providing a source of exogenous variation that helps to identify parental preferences.[73,74] In addition, the Australian child care subsidies changed over time, and the changes are assumed to be unanticipated by parents.[75] The changes in the child care subsidies also provide a source of identifying variation.[76] I also rely on functional form assumptions for identification. The utility and skill production functions are quadratic.

[72]Australian child care subsidies and income transfers are nationally implemented, so changes in these programs affect all households. As a result, it is difficult to find a proper comparison group because every family is treated.

[73]See Appendix A.2 for functional forms of the child care subsidies and income transfers.

[74]Similarly, Keane and Moffitt (1998) use highly nonlinear budget constraint generated by welfare programs in the US.

[75]The Australian income transfers also changed over time, but the changes are small. Nonetheless, I also use this variation for identification.

[76]Since there is no cross-state variation in Australian child care subsidies and income transfers, there is no comparison group available to serve as the basis for credible reduced form estimates of the effects of actual policy changes. Thus, it is infeasible to compare the simulated effects of the policy changes to the reduced form estimates, as in Blundell, Dias, Meghir and Shaw (2016), for example.

The terminal value function is assumed to have a different functional form from the utility function.

1.6 Estimation Results

1.6.1 Parameter Estimates

In Appendix A.6, Tables A.4 and A.5 show the full set of parameter estimates. I provide an overview of the production function parameter estimates because they are straightforward to interpret and are key to understanding the simulation results. In Table A.4, the parameters of the skill production functions are reported. The parameter estimates imply that cognitive and non-cognitive skills are self-productive and cross-productive, similar to the findings of Cunha et al. (2010) and Attanasio, Cattan, Fitzsimons, Meghir and Rubio-Codina (2018).[77] At preschool age, formal child care and paternal child care have a positive effect on cognitive skill development, and formal child care is more productive at zero hours in producing cognitive skill than father's child care.[78] Informal child care adversely affects cognitive skill development.[79] For non-cognitive skill, all types of non-maternal child care have negative effects on children. The negative productivity of formal child care is the

[77]Cunha et al. (2010) and Attanasio et al. (2018) estimate the production functions for cognitive and non-cognitive skills, and show evidence of the self-productivity of cognitive and non-cognitive skills. Cunha et al. (2010) also find the cross-productivity of non-cognitive skill on cognitive skill, but no cross-productivity of cognitive skill on non-cognitive skill. Attanasio et al. (2018) find a small cross-productivity effect of cognitive skill on non-cognitive skill, but no cross-productivity effect of non-cognitive skill on cognitive skill.

[78]Del Boca et al. (2014) show that paternal child care time is less productive than maternal child care time in child cognitive skill development. Mills-Koonce, Willoughby, Zvara, Barnett, Gustafsson, Cox and the Family Life Project Key Investigators (2015) find no evidence that mother's child care is a stronger predictor of child cognitive development than father's child care.

[79]Bernal and Keane (2011) and Chapter 2 of this dissertation find that informal child care has a negative effect on cognitive skill development. For the effect of formal child care, Bernal and Keane (2011) show a positive effect on cognitive skill, while I find a negative effect with a smaller effect than informal child care has. However, the effect of formal child care is imprecisely estimated in these studies.

largest at zero hours, and paternal child care has the smallest negative effect.[80,81] At school age, paternal child care and formal child care positively affect cognitive skill development, and informal child care has a negative effect on cognitive skill. For non-cognitive skill development, paternal child care has a very small positive effect, while formal and informal child care negatively affect non-cognitive skill. Monetary investment in children has positive effects on both types of skill development at both stages of childhood.

1.6.2 Model Fit

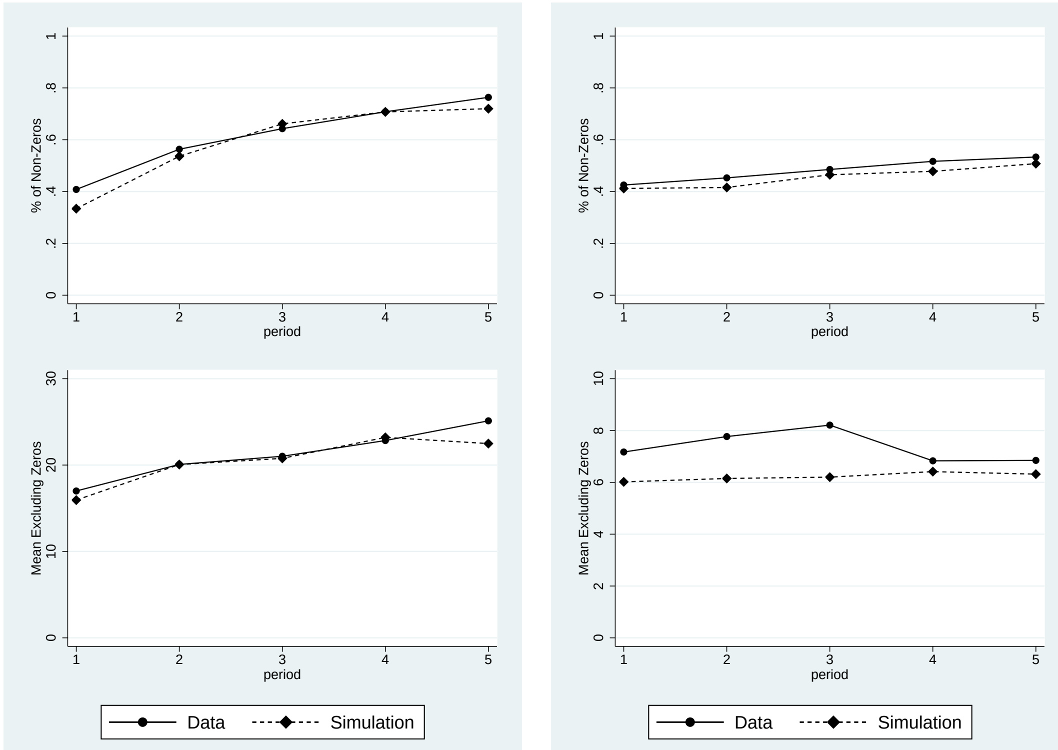
Figures 1.2 and 1.3 show model fit for parental choice variables.[82] In each subfigure, the upper graph shows the actual and simulated extensive margin for a corresponding choice variable from period 1 to period 5, and the lower graph shows the actual and simulated intensive margin for a corresponding choice variable from period 1 to period 5.

Panel (a) of Figure 1.2 shows the model fit to weekly hours of maternal work. The simulated fraction of working mothers closely captures the increasing trend of the actual fraction, but the model tends to underpredict in periods 1, 2 and 5. The largest gap between actual and simulated data is 7.4 percentage points in period 1. The simulated average weekly hours of maternal work is close to the actual mean hours of maternal work from period 1 to period 4, but the mean hours of maternal work is underpredicted by 2.6 hours (10.5%) in period 5.

[80]Magnuson et al. (2007) find similar results that pre-kindergarten in the US is associated with higher cognitive skill outcomes and higher behavior problems. The negative effect of non-parental child care on non-cognitive skill development could be because of child-parent separation, which could cause emotional or behavioral problems in children. Howard, Martin, Berlin and Brooks-Gunn (2011) show that early mother-child separation is associated with higher child negativity and aggression. Brumariu and Kerns (2010) review studies on parent-child attachment and internalizing problems such as anxiety and depression. They conclude that insecure attachment is related to higher levels of internalizing problems.

[81]Hours of maternal child care could include mother's time with the child outside home. For example, mothers could take their child to playground or neighbors where their children can meet other children and adults.

[82]In Appendix A.7, Figures A.5 and A.6 depict model fit by discretized values of parental choice variables.



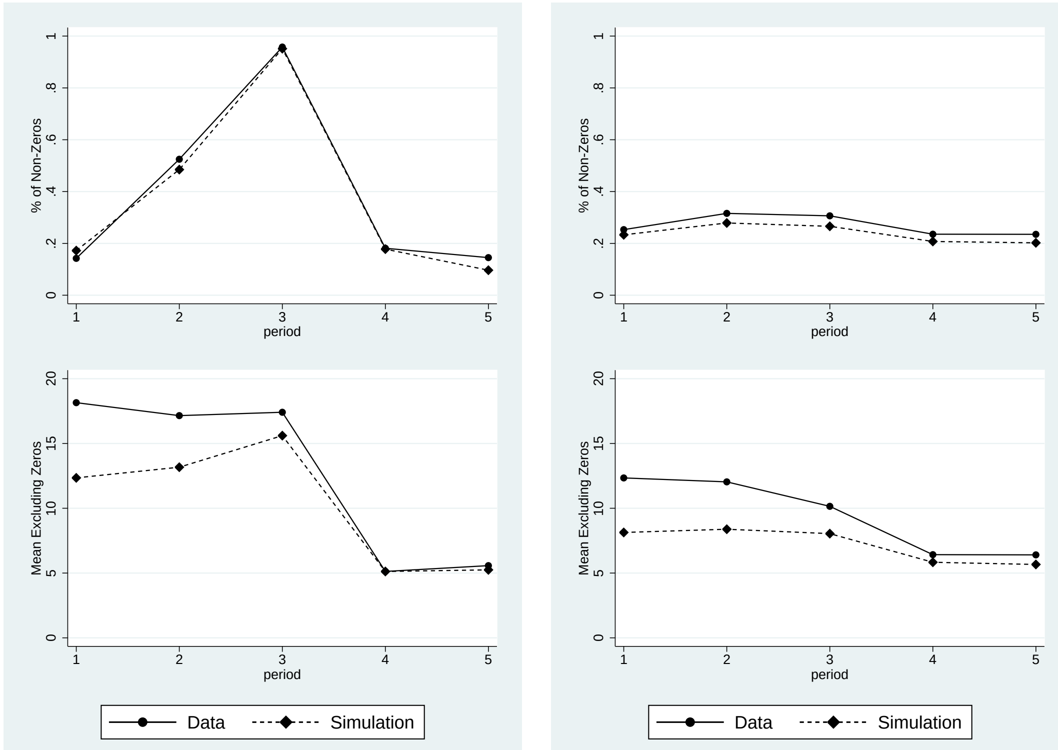
(a) Maternal Work (b) Paternal Child Care

Note: The upper graph shows the fraction of non-zeros (extensive margin), and the lower graph shows the mean of non-zeros (intensive margin).

Figure 1.2: Model Fit

The actual and simulated data for weekly hours of paternal child care are shown in Panel (b) of Figure 1.2. The model tends to underpredict the fraction of non-zero hours of paternal child care, with a maximum gap of 3.9 percentage points in period 4. The average weekly hours of paternal child care is underpredicted during preschooling periods. The gap between the actual and simulated data ranges from 1.2 to 2.0 hours (or from 16.1% to 24.5%).

The model fit to weekly hours of formal child care is shown in Panel (a) of Figure 1.3. The simulated extensive margin of formal child care closely follows the observed pattern



(a) Formal Child Care (b) Informal Child Care

Note: The upper graph shows the fraction of non-zeros (extensive margin), and the lower graph shows the mean of non-zeros (intensive margin).

Figure 1.3: Model Fit

that increases during preschooling periods and decreases after school entry. The largest gap between the actual and simulated fraction of non-zero hours is 4.9 percentage points in period 5. The model underpredicts the mean hours of formal child care by 5.8 hours (32.0%) in period 1 and by 4.0 hours (23.2%) in period 2.[83]

In Panel (b) of Figure 1.3, the actual and simulated weekly hours of informal child care are shown. The fraction of children with informal child care tends to be underpredicted by 2.0 to 4.0 percentage points. The average hours of informal child care also tends to

[83]This is mainly because the model underpredicts the fraction for 38 hours of formal child care during preschooling periods. See Panel (a) of Figure A.6 in Appendix A.7.

be underpredicted. There are large gaps between the actual and simulated mean hours in periods 1 and 2: 4.2 hours (34.1%) and 3.7 hours (30.4%), respectively. The gaps in periods 3 to 5 are relatively smaller.[84]

To sum up, there are some gaps between the simulated and observed patterns in the intensive margin for each type of child care. However, the model closely captures the main patterns of the extensive margins of parental choice variables, and predicts quite well the distribution of hours of each choice variable, as shown in Figures A.5 and A.6 in Appendix A.7. Thus, the overall model fit to the data is reasonably good.[85]

1.7 Counterfactual Experiments

In this section, I use the model to conduct counterfactual policy experiments to evaluate the effects of child care subsidies for formal child care and income transfers.[86] I consider child care subsidies and income transfers for ages 0 to 5, and conduct policy experiments under three different program restrictions. First, there is no restriction to receive the benefits (i.e., no maternal work requirement and income eligibility), so formal child care and income transfer are universal programs. Second, there is a maternal work requirement, that is, mothers must work to receive the benefits. Two cases are considered: any employment (i.e., weekly hours of work more than 0) and part-time work (i.e., weekly hours of work more

[84]The large gaps in the first two periods are because the model underpredicts the fraction of higher discrete values of informal child care time (24 and 38 hours). See Panel (b) of Figure A.6 in Appendix A.7.

[85]In Appendix A.7, Table A.6 shows the model fit to other variables such as the number of children, work experience, maternal hourly wage, paternal weekly earnings, child's cognitive and non-cognitive skills, and school quality. Generally, the simulated means are close to the actual means. However, the model underpredicts maternal hourly wage and paternal weekly earnings. The actual average of accepted maternal wage is 39.99 AUD per hour for preschooling periods and 37.94 AUD for schooling periods, but the simulated accepted wage means are 36.36 AUD (a gap of 8.6%) for preschooling periods and 32.71 AUD (a gap of 13.8%) for schooling periods. The simulated mean of paternal weekly earnings is smaller by 146 AUD (a gap of 8.2%) than the actual mean for preschool periods and by 183 AUD (a gap of 10.0%) for schooling periods.

[86]I consider child care subsidies for only formal child care because governments generally provide subsidies for formal child care, which is approved and regulated by the governments.

than 15) requirements. Third, the benefits are income tested, that is, family income must be below an income cutoff for families to be eligible to receive the benefits. Three cutoffs are considered: 1,500 AUD, 2,000 AUD, and 2,500 AUD. For every policy experiment, I make two assumptions: (1) tax rates are fixed at the 2012–13 rates, and (2) parents are aware that the corresponding policy is fixed for all periods. For comparison, I use a benchmark where there is no child care subsidy and income transfer.

1.7.1 Effects of Child Care Subsidy

Table 1.2 reports the effects of a 100% child care subsidy on child skill development and parental behavior. Column 1 shows the benchmark levels: means of cognitive and non-cognitive skills at ages 10 to 11 (terminal period), fractions of non-zeros for each choice variable at preschool age (ages 0 to 5), average hours of each choice variable at preschool age excluding zeros, mean expenditure on children and consumption at preschool age, and average lifetime household utility. Columns 2 to 7 show the results of each child care subsidy scenario. The values for cognitive and non-cognitive skills in these columns are differences from the benchmark (Column 1), and the values for other variables are percentage changes from the benchmark. For purposes of interpretation, cognitive and non-cognitive skills in the benchmark are renormalized with a mean of zero and a standard deviation of one. In all other scenarios, cognitive and non-cognitive skills are then renormalized, using the same normalization as in the benchmark.

Column 2 of Table 1.2 shows the results for the 100% child care subsidy with no restriction (universal formal child care). Universal formal child care at preschool age has a positive effect on cognitive skill. The average cognitive skill at ages 10 to 11 is larger by 0.0111 standard deviations compared to the benchmark. However, there is a negative effect

	Benchmark	Difference/Percentage Change from Benchmark					
		No	Work Requirement		Income Eligibility		
		Restriction	> 0 hours	> 15 hours	< $ 1,500	< $ 2,000	< $ 2,500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government Spending per Week	-	$ 514,006	$ 437,108	$ 352,590	$ 100,859	$ 217,132	$ 317,320
Cognitive Skill at Ages 10-11	0.0000	0.0111	0.0039	-0.0005	0.0050	0.0082	0.0102
Non-Cognitive Skill at Ages 10-11	0.0000	-0.0113	-0.0080	-0.0055	-0.0031	-0.0058	-0.0080
Maternal Employment at Preschool Age	53.6%	1.0%	2.0%	0.0%	0.2%	0.5%	0.7%
Paternal Child Care at Preschool Age	41.8%	-1.5%	-1.6%	-1.1%	-0.1%	-0.6%	-0.9%
Formal Child Care at Preschool Age	44.2%	41.4%	28.8%	9.0%	14.1%	25.5%	33.0%
Informal Child Care at Preschool Age	29.6%	-5.6%	-5.6%	-3.5%	-1.4%	-2.6%	-3.3%
Hours of Maternal Work at Preschool Age	18.4	0.4%	-0.1%	1.9%	-0.4%	-0.4%	-0.3%
Hours of Maternal Child Care at Preschool Age	79.2	-5.3%	-4.0%	-2.8%	-1.4%	-2.7%	-3.8%
Hours of Maternal Leisure at Preschool Age	22.7	18.0%	13.2%	8.9%	4.9%	9.5%	12.9%
Hours of Paternal Child Care at Preschool Age	6.1	-1.2%	-1.1%	-0.5%	-0.2%	-0.5%	-0.9%
Hours of Formal Child Care at Preschool Age	13.3	18.9%	19.0%	34.1%	-0.8%	4.4%	9.1%
Hours of Informal Child Care at Preschool Age	8.4	-0.9%	-0.9%	-1.3%	0.1%	-0.1%	-0.5%
Expenditure on Child at Preschool Age	$ 188	0.2%	0.3%	0.3%	0.0%	0.0%	0.1%
Consumption at Preschool Age	$ 1,250	3.9%	3.7%	3.3%	0.5%	1.3%	2.1%
Lifetime Utility	6.593	1.6%	1.4%	1.1%	0.4%	0.7%	1.1%

Note: Benchmark is a scenario without child care subsidy and income transfer. No Restriction is a child care subsidy scenario without a work requirement and income test. Work Requirement is a child care subsidy scenario with a minimum work hours requirement for mothers. Income Eligibility is a child care subsidy scenario with income cutoffs. The values in Column 1 are averages in Benchmark. Cognitive and Non-Cognitive skills are restandardized, using Benchmark's means and standard deviations. The symbol '$' indicates the Australian dollar. Lifetime utility is the sum of discounted utility at period 1, measured in Australian dollars.

Table 1.2: Effects of 100% Child Care Subsidy for Ages 0-5

on non-cognitive skill. The average non-cognitive skill at ages 10 to 11 is lower by 0.0113 standard deviations, compared to the benchmark.[87]

The effects on the skills of children are largely driven by an increase in use of formal child care. The fraction of households that use formal child care at preschool age is larger by 41.4% (18.3 percentage points). Parents also use formal child care for more hours with the universal formal child care. The average hours of formal child care at preschool age is 18.9% (2.5 hours per week) greater than in the benchmark. While child care subsidy has a large effect on formal child care use, it has small negative effects on paternal and informal child care during preschooling periods. This implies that parents substitute formal child care for maternal child care. As we have seen in Section 1.6.1, the productivity of formal child care is positive for cognitive skill and negative for non-cognitive skill, so the large increase in use of formal child care results in an increase in cognitive skill and a decrease in non-cognitive skill.

Column 2 shows that the universal formal child care subsidy generates little incentive for maternal work. Compared to the benchmark, the percentage of working mothers at their child's ages 0 to 5 increases by 1.0%, and the average weekly hours of maternal work increases by 0.4%. This implies that mothers allocate additional free time resulting from using more formal child care and less maternal child care mostly to their leisure rather than work. The effects of the universal formal child care subsidy on the intensive margins show evidence of this. The average weekly hours of maternal child care at preschool age is

[87] In Appendix A.8, Table A.7 shows the effects of the 100% child care subsidy on skills at each schooling period. The effects are largest at ages 6 to 7 (0.0249 standard deviations for cognitive skill and -0.0352 for non-cognitive skill) and depreciate as children age.

5.3% (4.2 hours per week) smaller, while the average weekly hours of maternal leisure at preschool age is 18% (4.1 hours per week) greater.[88]

The results for the 100% child care subsidy with a maternal work requirement are reported in Columns 3 and 4 of Table 1.2. Generally, the patterns of the effects are similar to the patterns in the no restriction scenario, but the magnitude of the effects is smaller. This is partly because the number of beneficiaries is smaller in the restriction scenario that in the no restriction scenario. When maternal employment is a requirement for child care subsidy (Column 3), cognitive skill at ages 10 to 11 increases by 0.0039 standard deviations, and non-cognitive skill decreases by 0.0080 standard deviations. The effect on formal child care use is also smaller with the employment requirement than with no restriction. In the scenario with part-time work requirement (Column 4), the effect on cognitive skill is negative and very small (-0.0005 standard deviations), and the effect on non-cognitive skill is -0.0055 standard deviations, which is smaller than the effect on non-cognitive skill in the scenario with employment requirement. The effect on formal child care on the extensive margin is also smaller with the part-time work requirement than with the employment requirement, but there is a larger effect on the intensive margin. Compared to the benchmark, the average weekly hours of formal child care at preschool age is greater by 34.1%, more than the effect in the scenario with employment requirement. Despite this larger intensive margin effect on formal child care, the child care subsidy with part-time work requirement has smaller effects on children's skills than the subsidy with employment requirement. This suggests

[88]The small effect on maternal work is consistent with the findings of Fitzpatrick (2010) and Havnes and Mogstad (2011a). Fitzpatrick (2010) studies the effect of universal preschool programs in the US states of Georgia and Oklahoma and finds a positive effect on preschool enrollment but little effect on maternal labor supply. Havnes and Mogstad (2011a) examine the effect of child care subsidy expansions in Norway, and show that there is little effect on maternal employment. In a survey study by Blau and Currie (2006), the authors also report that the best available estimates for the elasticity of maternal labor supply with respect to child care price are small.

that the impacts on children's skills are mainly from changes in the extensive margin of formal child care, not from changes in the intensive margin.

One notable result is that there is only a small effect of child care subsidy on maternal work despite the work requirement. With maternal employment requirement, the child care subsidy has a small positive effect on the extensive margin of maternal work (2.0%), and there is a very small effect on the intensive margin. When mothers must work for more than 15 hours per week to be eligible for the child care subsidy (part-time work requirement), there is a small positive effect on the intensive margin (1.9%) but no effect on the extensive margin. This suggests that incorporating a maternal work requirement to a child care subsidy does not generate a strong incentive to work for mothers, and many eligible mothers would work even if child care subsidy had no maternal work requirement.

Columns 5 to 7 of Table 1.2 show the results for the 100% child care subsidy with family income eligibility restrictions. The patterns of the effects are similar to those in the scenario without restriction, but the magnitude of the effects is smaller. With a 1,500 AUD cutoff, the average cognitive skill at ages 10 to 11 is larger by 0.0050 standard deviations than the benchmark, and the average non-cognitive skill at ages 10 to 11 is smaller by 0.0031 standard deviations. As the income cutoff increases, the effects become greater since more households become eligible. There is a positive effect on formal child care use. Compared to the benchmark, the fractions of households that use formal child care at ages 0 to 5 are larger by 14.1%, 25.5%, and 33.0% for 1,500 AUD, 2,000 AUD, and 2,500 AUD cutoffs, respectively. For maternal employment, paternal child care and informal child care, the effects are small.[89]

[89] I also consider child care subsidies with a phase-out rate. In Appendix, Table A.8 shows the results for child care subsidies with a phase-out rate that reduces the subsidy rate by 0.1% for each dollar over an income cutoff, and the results are similar to the main results.

Comparing the child care subsidy with 2,500 AUD family income cutoff (Column 7) and the subsidy with no restriction (Column 2) shows an interesting result. Although the government spends 38.3% less in the income eligibility scenario than in the no restriction scenario, the positive effect on cognitive skill is only 8.1% smaller, and the negative effect on non-cognitive skill is 29.2% smaller. This suggests that a child care subsidy program is more cost-effective for improving the cognitive skill of children if the program focuses on lower income families.[90] This result is because lower income families are less likely to use formal child care in the absence of the child care subsidy, but increase use of formal child care by more than higher income families.

Comparing the subsidy scenarios with income eligibility and the scenarios with a maternal work requirement, I also find that child care subsidies with income eligibility are more cost-effective for improving the skills of children than the subsidy with a maternal work requirement. For example, compared to the scenario with maternal employment requirement (Column 3), the government spends less by 27.4% in the income eligibility scenario with a 2,500 AUD cutoff (Column 7), but the effect on cognitive skill is 162% greater and the effect on non-cognitive skill is the same. I find a similar result when comparing the child care subsidy with a part-time work requirement (Column 4) to the subsidy with a 1,500 AUD income cutoff (Column 5). These results are because the child care subsidy with income eligibility targets families who would use no or less formal child care due to low income. These families would significantly respond to the child care subsidy, especially on the extensive margin. For example, the fraction of families who use formal child care increases by 28.8% with the employment requirement, but by 33.0% with the 2,500 AUD

[90] I examine the effects of child care subsidies, holding government spending constant. For this purpose, I set the government spending equal to the total cost of a 30% child care subsidy for formal child care with no restriction, and then adjust the rate of child care subsidy to have this government spending for each scenario. Table A.9 in Appendix A.8 reports the results, which reconfirm the findings from the main results.

income cutoff.[91] These results reinforce the importance of targeting lower income families for the design of child care subsidies to improve children's skills, even without considering equity issues.

1.7.2 Effects of Income Transfer

Table 1.3 shows the effects of an income transfer on child skill development and parental behavior. The income transfer amount considered is 240 AUD per week, which is equivalent to the cost of 30 hours of formal child care ($p_{fc} \times 30 = 240$). Column 1 of Table 1.3 shows averages in the benchmark. Columns 2 to 7 report the results of each income transfer scenario, and the values in these columns are differences or percentage changes from the benchmark. Cognitive and non-cognitive skills are renormalized in the same way as in the previous section.

Column 2 of Table 1.3 reports the results for an income transfer with no restriction (universal income transfer). The income transfer has positive effects on both cognitive and non-cognitive skill development. The average cognitive and non-cognitive skills at ages 10 to 11 are 0.0092 and 0.0142 standard deviations greater than the benchmark, respectively.[92] The universal income transfer has a small negative effect on maternal work, with a decrease of 1.2%. There is a positive effect on use of formal child care, but the effect is also small, with increases of 1.3% and 1.1% on the extensive and intensive margins, respectively. The effects of the income transfer on paternal and informal child care are very small. The main source of the positive effects on skills is, therefore, an increase in expenditures on children. Parents invest, on average, 15.8% (30 AUD) more in child skill development when the universal

[91] Child care subsidies at different rates are also examined. The results are qualitatively similar, but the size of the effects is smaller than the results in Table 1.2 because of smaller subsidy rates.

[92] Table A.10 in Appendix A.8 reports the effects of the income transfer at each period of school age. The effects on cognitive and non-cognitive skills at ages 6 to 7 are 0.0124 and 0.0362 standard deviations, respectively. The effects depreciate as children age.

		Difference/Percentage Change from Benchmark					
	Benchmark	No	Work Requirement		Income Eligibility		
		Restriction	> 0 hours	> 15 hours	< $ 1,500	< $ 2,000	< $ 2,500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government Spending per Week	-	$ 1,510,965	$ 901,883	$ 526,178	$ 543,430	$ 918,416	$ 1,167,847
Income Transfer Rate	-	$ 240	$ 240	$ 240	$ 240	$ 240	$ 240
Cognitive Skill at Ages 10-11	0.0000	0.0092	0.0075	0.0041	0.0031	0.0055	0.0072
Non-Cognitive Skill at Ages 10-11	0.0000	0.0142	0.0096	0.0055	0.0049	0.0085	0.0109
Maternal Employment at Preschool Age	53.6%	-1.2%	11.4%	0.0%	-2.9%	-2.7%	-1.8%
Paternal Child Care at Preschool Age	41.8%	-0.1%	0.3%	-0.04%	-0.2%	-0.1%	-0.1%
Formal Child Care at Preschool Age	44.2%	1.3%	5.1%	3.2%	-0.6%	-0.3%	0.2%
Informal Child Care at Preschool Age	29.6%	-0.1%	1.2%	0.3%	-0.1%	-0.5%	-0.4%
Hours of Maternal Work at Preschool Age	18.4	-0.1%	-6.4%	3.5%	0.4%	0.1%	-0.9%
Hours of Maternal Child Care at Preschool Age	79.2	-0.2%	-0.4%	-0.4%	0.1%	0.05%	0.03%
Hours of Maternal Leisure at Preschool Age	22.7	1.1%	-0.6%	-0.1%	0.9%	1.0%	1.1%
Hours of Paternal Child Care at Preschool Age	6.1	-0.2%	-0.1%	0.1%	-0.01%	-0.2%	-0.2%
Hours of Formal Child Care at Preschool Age	13.3	1.1%	-1.7%	2.0%	0.1%	-0.5%	-0.3%
Hours of Informal Child Care at Preschool Age	8.4	-0.02%	-0.2%	0.1%	0.0%	0.1%	-0.02%
Expenditure on Child at Preschool Age	$ 188	15.8%	10.3%	6.1%	5.4%	9.3%	11.9%
Consumption at Preschool Age	$ 1,250	16.4%	10.5%	6.1%	5.6%	9.7%	12.4%
Lifetime Utility	6.593	7.7%	3.9%	2.1%	3.0%	5.0%	6.2%

Note: Benchmark is a scenario without child care subsidy and income transfer. No Restriction is an income transfer scenario without work requirement and income test. Work Requirement is an income transfer scenario with a minimum work hours requirement for mothers. Income Eligibility is an income transfer scenario with income cutoffs. A value of $240 of income transfer is an equivalent amount to the cost of 30 hours of formal child care. The values in Column 1 are averages in Benchmark. Cognitive and Non-Cognitive skills are restandardized, using Benchmark's means and standard deviations. The symbol '$' indicates the Australian dollar. Lifetime utility is the sum of discounted utility at period 1, measured in Australian dollars.

Table 1.3: Effects of Income Transfer for Ages 0-5

income transfer is available at preschool age.[93] Monetary investment positively affects both types of skill development, as discussed in Section 1.6.1, so the increase in expenditures on children results in increases in cognitive and non-cognitive skills. Lastly, the income transfer affects households' consumption. Average weekly consumption at preschool age increases by 205 AUD, which is 85% of the income transfer benefit. Thus, the income transfer is mostly allocated to consumption rather than to purchasing inputs to child skill production including non-parental child care.[94]

Columns 3 and 4 in Table 1.3 show the results for income transfers with a maternal work requirement. The effects on cognitive and non-cognitive skills are smaller than the effects in the no restriction scenario (Column 2), which is partly because of a smaller number of beneficiaries. With a maternal employment requirement (Column 3), the income transfer has a positive effect on the maternal employment rate, with an increase of 11.4%. Moreover, the number of mothers who use formal child increases by 5.1%. The average hours of maternal work decreases by 6.4%, mainly because mothers who are induced to work by the income transfer work for only a small number of hours, just to satisfy the employment requirement. With a part-time work requirement (Column 4), the income transfer increases the hours of maternal work by 3.5% but has no effect on the maternal employment rate. There are positive effects on use of formal child care, with an increase of 3.2% and 2.0% on the extensive margin and intensive margin, respectively. As in the universal income transfer, the improvements in cognitive and non-cognitive skills are largely due to an increase in expenditure on children. However, the effect on maternal work also partly explains the improvements in cognitive and non-cognitive skills, because mothers

[93] This result is based on a parameter estimate: the fraction of net family income used for child skill development. The fraction is estimated under the assumption that it is a constant.

[94] Consumption includes goods that presumably benefit children, such as food, clothing, and shelter, but have no direct effect on skill development.

bring additional income from their work to households, so expenditure on children also increases. In addition, the increase in cognitive skill is partly explained by the increase in use of formal child care.

Columns 5 to 7 show the results for income transfer scenarios with family income eligibility restrictions. The patterns of effects on children and parents are generally similar to those in the no restriction scenario (Column 2), except for the smaller size of the effects. There are positive effects on cognitive and non-cognitive skills, and the effects are larger when the income cutoff is higher. Compared to the benchmark, the average cognitive skill at ages 10 to 11 is 0.0031 to 0.0072 standard deviations greater, and the average non-cognitive skill at ages 10 to 11 is 0.0049 to 0.0109 standard deviations greater. There is a decrease of 1.8% to 2.9% in the maternal employment rate. The effects on paternal child care, formal child care, and informal child care are very small. Therefore, the positive effects on skills are due to an increase in expenditure on children.[95]

One interesting result comes from the comparison of the income transfer with a maternal employment requirement (Column 3) and the income transfer with a 2,000 AUD income cutoff (Column 6). In the scenario with the employment requirement, the government spends 16,533 AUD per week (or 1.8%) less than in the income eligibility scenario, but the improvements in cognitive and non-cognititve skills are 36% and 13% greater, respectively. Comparing the scenario with a part-time work requirement (Column 4) with the scenario with a 1,500 AUD income cutoff (Column 5) leads to a similar result.[96] This suggests that

[95]In Appendix A.8, Table A.11 reports the results with a phase-out rate. A 30% phase-out for each dollar over an income cutoff is considered. The results are similar to the main results.

[96]The effects of income transfers with different restrictions are also examined, holding government spending constant. Government spending in the income transfer scenario with no restriction (Column 2 in Table 1.3) is used as the target budget of the government, so the income transfer amount is adjusted to have this target budget for each scenario. In Appendix A.8, the results reported in Table A.12 reinforce the findings from the main results. The scenarios with a maternal work requirement have larger effects on cognitive and non-cognitive skills than the scenarios with income eligibility.

	Benchmark (1)	Difference/ Percentage Change from Benchmark: Child Care Subsidy (2)	Income Transfer (3)
Government Spending per Week	-	$ 514,006	$ 514,006
Child Care Subsidy Rate or Income Transfer Rate	-	100%	$ 82
Cognitive Skill at Ages 10-11	0.0000	0.0111	0.0032
Non-Cognitive Skill at Ages 10-11	0.0000	-0.0113	0.0049

Note: Benchmark is a scenario without child care subsidy and income transfer. Child Care Subsidy and Income Transfer are scenarios with no maternal work requirement and income test. The subsidy rate is 100% in Child Care Subsidy scenario. The values in Column 1 are averages in Benchmark. Cognitive and Non-Cognitive skills are restandardized, using Benchmark's means and standard deviations. The symbol '$' indicates the Australian dollar.

Table 1.4: Comparison between Child Care Subsidy and Income Transfer

a maternal work requirement is important for the design of an effective income transfer program for improving children's skills. This can be explained as follows: While income eligibility discourages work, a maternal work requirement incentivizes mothers to work and use formal child care more. As a result, there are greater improvements in the skills of children.

1.7.3 Comparison between Free Formal Child Care and Income Transfer

In this section, the effects of child care subsidy and income transfer programs are compared. For an effective comparison, the amount of government spending is held constant. I first simulate the model for a child care subsidy, and calculate the total cost of the subsidy. The income transfer amount is then chosen to set the government spending equal to the total cost of the subsidy.

Table 1.4 shows the effects of the two programs with no restriction.[97] Column 2 shows the results for a 100% child care subsidy without restriction (universal formal child care), and Column 3 reports the results for an income transfer without restriction (universal income transfer). As shown in the first row, government spending is the same under these

[97]See Table A.13 in Appendix A.8 for the results about other variables.

two scenarios, and the amount of the universal income transfer is set at 82 AUD to have the same government budget. A comparison of Columns 2 and 3 reveals that the effect on children's cognitive skill of the universal formal child care is more than three times greater than the effect of the universal income transfer (0.0111 versus 0.0032). However, the universal formal child care has a negative effect on non-cognitive skill (-0.0113), while the universal income transfer positively affects the development of non-cognitive skill (0.0049). Therefore, the comparison of child care subsidy and income transfer programs suggests that there exists a trade-off between these two policies: child care subsidies improve cognitive skill by more with less government spending, but non-cognitive skill worsens, whereas income transfers boost both cognitive and non-cognitive skills, but the positive effect on cognitive skill is smaller than the effects of child care subsidies.[98]

1.7.4 Optimal Policy

The counterfactual experiments in the previous sections provide useful implications for the designs of child care subsidy and income transfer programs. Child care subsidies are useful for improving children's cognitive skill, and they are more effective if they target lower income families. Income transfers increase both the cognitive and non-cognitive skills of children, and a maternal work requirement is important for the effectiveness of the program. However, child care subsidies adversely affect the development of non-cognitive skill, and income transfers have relatively small effects on children's skills. This trade-off motivates me to consider the design of an optimal mix of the two programs to maximize the improvements in the children's cognitive and non-cognitive skills.

[98]The results under other restrictions (i.e., work requirement and income eligibility) are similar to the results under no restriction. See Table A.14 in Appendix A.8.

It is assumed that the goal of a social planner is to maximize the improvement in a weighted average of cognitive and non-cognitive skills of children at the terminal period (ages 10 to 11). The objective function for the social planner is given by

$$\omega(\Theta_c - \bar{\Theta}_c) + (1-\omega)(\Theta_n - \bar{\Theta}_n), \tag{1.21}$$

where ω is a weight on cognitive skill; Θ_c and Θ_n are average cognitive and non-cognitive skills at ages 10 to 11 in the optimal policy, respectively; and $\bar{\Theta}_c$ and $\bar{\Theta}_n$ are average cognitive and non-cognitive skills at ages 10 to 11 in the benchmark (no subsidy and income transfer), respectively.[99]

The choice of ω is based on the result of Cunha et al. (2010). They find that 16% of the variation in educational attainment at age 19 is explained by cognitive skill and 12% is explained by non-cognitive skill. I use this result to set ω at 0.57 ($= \frac{16\%}{16\%+12\%}$). Therefore, the objective function of the social planner could be interpreted as maximizing children's educational attainment. I also examine two alternative assumptions on the weights: a 25% weight on cognitive skill and 75% on non-cognitive skill, and a 75% weight on cognitive skill and 25% on non-cognitive skill.

The social planner chooses the following policy parameters: a child care subsidy rate, s%; an income transfer rate, b AUD per week; a maternal work requirement, wr_s for the child care subsidy and wr_t for the income transfer, where $wr_j = 0$ for no maternal work requirement, $wr_j = 1$ for hours of work per week more than 0, and $wr_j = 2$ for hours of work per week more than 15, for $j = s, t$; and income eligibility cutoffs, E_s AUD per week for the child care subsidy and E_t AUD per week for the income transfer. The government

[99] Parental utility is not in the objective function since the optimal policy considered here is aimed at improving child skill development.

	Child Care Subsidy	Income Transfer
Government Spending per Week	\$ 51,739 6.9%	\$ 694,515 93.1%
Rate	61%	\$ 258
Maternal Work Requirement	No	Yes (more than 0 hour)
Income Cutoff	\$ 1,515	\$ 2,590

Note: Total government spending per week is 746,254 AUD. The symbol '\$' indicates the Australian dollar. The weight on cognitive skill (ω) is 0.57.

Table 1.5: Optimal Mix of Child Care Subsidy and Income Transfer

budget constraint is given by

$$S(s, wr_s, E_s) + T(b, wr_t, E_t) \leq \bar{G}, \tag{1.22}$$

where $S(\cdot)$ is child care subsidy budget, $T(\cdot)$ is income transfer budget, and $\bar{G}$ is total budget for the child care subsidy and income transfer programs.

To get a realistic value for the government budget, I simulate the model based on the 2012–13 Australian policy for child care subsidies and income transfers, and calculate the total spending on subsidies and income transfers for all periods. The simulated total per-week spending on these public programs is 746,415 AUD, and the Australian government uses 34.7% for child care subsidies (259,271 AUD) and 65.3% for income transfers (487,144 AUD).

The social planner's maximization problem is solved in two steps. First, a set of four continuous policy parameters (s, b, E_s, and E_t) that maximizes the objective function in (1.21) is chosen, conditional on parameters for maternal work requirement (wr_s and wr_t).[100] Then, I choose wr_s and wr_t with the largest objective function value.

[100] A simplex method developed by Nelder and Mead (1965) is used to find the maximum.

Table 1.5 shows the optimal choice of policy parameters with a 57% weight on cognitive skill and 43% weight on non-cognitive skill. The derived features of the optimal policy are consistent with the findings presented in the previous sections. The optimal policy allocates 6.9% of government budget to the child care subsidy program and the rest to the income transfer program. The small fraction of the budget allocated to child care subsidy is justified by its negative effect on non-cognitive skill; therefore the child care subsidy focuses on children who benefit the most, that is, children in low income families. The child care subsidy covers 61% of the cost of formal child care. There is no maternal work requirement to be eligible for the subsidy, and it serves low income families with family income below 1,515 AUD per week. The optimal policy allocates a larger proportion of public funds to the income transfer. This transfer provides households with 258 AUD of cash per week. Maternal employment is required to be eligible for the income transfer. Households must have an income less than 2,590 AUD per week for the income transfer benefit, so both middle and low income families are eligible for the benefit. Thus, the optimal income transfer has two roles: (1) to offset the negative effect of the child care subsidy on non-cognitive skill for children in low income families, and (2) to boost both types of skills for children in middle and low income families.

Table 1.6 reports the effects of the optimal policy (Column 2) and the 2012–13 Australian policy (Column 3). The 2012–13 policy has a larger positive effect on cognitive skill than the optimal policy (0.0144 versus 0.0098 standard deviations); the effect of the 2012–13 policy on non-cognitive skill is negative (-0.0024 standard deviations), while the effect of the optimal policy is positive (0.0056 standard deviations). This is because the 2012–13 policy provides child care subsidies for middle and high income families as well as low income families, so it allocates government budget to the subsidies more than the optimal policy.

	Benchmark (1)	Optimal Policy (2)	2012–13 Policy (3)
Government Spending per Week	-	$ 746,254	$ 746,415
Child Care Subsidy	-	$ 51,739	$ 259,271
Income Trasfer	-	$ 694,515	$ 487,144
Cognitive Skill at Ages 10-11	0.0000	0.0098	0.0144
Non-Cognitive Skill at Ages 10-11	0.0000	0.0056	-0.0024
Maternal Employment at Preschool Age	53.6%	11.0%	-3.8%
Paternal Child Care at Preschool Age	41.8%	0.2%	-1.1%
Formal Child Care at Preschool Age	44.2%	13.6%	24.3%
Informal Child Care at Preschool Age	29.6%	0.1%	-2.8%
Hours of Maternal Work at Preschool Age	18.4	-7.4%	2.7%
Hours of Maternal Child Care at Preschool Age	79.2	-1.1%	-2.9%
Hours of Maternal Leisure at Preschool Age	22.7	2.7%	10.7%
Hours of Paternal Child Care at Preschool Age	6.1	-0.2%	-0.7%
Hours of Formal Child Care at Preschool Age	13.3	-4.1%	8.4%
Hours of Informal Child Care at Preschool Age	8.4	-0.3%	-0.3%
Expenditure on Child at Preschool Age	$ 188	7.8%	3.4%
Consumption at Preschool Age	$ 1,250	8.2%	5.1%
Lifetime Utility	6.593	3.3%	3.6%

Note: Benchmark is a scenario without child care subsidy and income transfer. The values under Benchmark are averages. The values under Optimal Policy and 2012–13 Policy are differences or percentage changes from Benchmark. Cognitive and Non-Cognitive skills are restandardized, using Benchmark's means and standard deviations. The symbol '$' indicates the Australian dollar. Lifetime utility is the sum of discounted utility at period 1, measured in Australian dollars.

Table 1.6: Effects of Optimal Policy and 2012–13 Policy

Consistent with this result, the fraction of households using formal child care increases by more for the 2012–13 policy than for the optimal policy (24.3% versus 13.6%). Moreover, the 2012–13 policy has a positive effect on the intensive margin of formal child care use (8.4%), while the optimal policy has a negative effect (-4.1%).[101] The optimal policy spends more government budget on the income transfer than the 2012–13 policy, so expenditure on children increases by more for the optimal policy (7.8% versus 3.4%). Consequently, the optimal policy has a positive effect on non-cognitive skill, which implies that the positive effect of the optimal income transfer on non-cognitive skill is larger than the adverse effect of the optimal child care subsidy. The increase in expenditure on children is also partly explained by the increase in maternal employment. The optimal policy increases maternal employment by 11.0%, while the 2012–13 policy decreases maternal employment by 3.8%. This is mainly because the optimal income transfer has a maternal employment requirement, but maternal work is not required for the 2012–13 income transfer. Interestingly, there is a negative effect on the intensive margin of maternal work for the optimal policy (-7.4%) and a positive effect for the 2012–13 policy (2.7%). The negative effect for the optimal policy is explained by two factors: First, mothers who are newly employed work fewer hours just to satisfy the employment requirement. Second, some working mothers work fewer hours to satisfy the family income restrictions for the child care subsidy and income transfer. The positive effect for the 2012–13 policy is because mothers who are induced by the policy to be unemployed work fewer hours.

In Appendix A.8, Table A.15 shows how the design of the optimal policy mix differs by the values of the weight, ω. When the weight on cognitive skill is greater, it is optimal

[101] The negative effect can be explained by the reduction in hours of maternal work and by the fact that children in households who are induced by the policy to use formal child care spend fewer hours in formal child care.

to allocate more funds to a child care subsidy by increasing the subsidy rate and income cutoff. As discussed above, the optimal policy with the 57% weight on cognitive skill allocates 6.9% of the government budget to the child care subsidy. As indicated by the results in Table A.15, the optimal policy spends nothing on the child care subsidy when the weight on cognitive skill is 25%, but spends 30.8% of public funds on the child care subsidy when the weight on cognitive skill is 75%. Table A.16 shows the results for the effects of the optimal policy with 25% and 75% weight on cognitive skill. Column 2 of Table A.16 indicates that the optimal policy with a 25% weight on cognitive skill has positive effects on both types of children's skills, but there is a 24% larger improvement in non-cognitive skill than in cognitive skill. Compared to the results of the optimal policy with the 57% weight on cognitive skill (Column 3 of Table A.16), the improvement in non-cognitive skill is 46% greater for the policy with the 25% weight on cognitive skill, but the improvement in cognitive skill is 33% smaller. Column 4 of Table A.16 reports the results for the effects with a 75% weight on cognitive skill. There is a positive effect on cognitive skill, and it is 34% greater than the effect when the weight on cognitive skill is 57%. However, the effect on non-cognitive skill is negative and small (-0.0005 standard deviations).

1.8 Conclusion

In this chapter, I structurally estimate a model of parental choice of labor supply and child care jointly with child cognitive and non-cognitive skill production functions. The estimated model is used to analyze the effects of child care subsidy and income transfer programs on children's cognitive and non-cognitive skills, and to simulate the optimal mix of these two types of programs. The results suggest several important implications. Child care subsidies targeting lower income families are more cost-effective for improving child cognitive skill development, but have a negative effect on non-cognitive skill development. Therefore, it is optimal to allocate a relatively smaller fraction of public funds to child care subsidies by focusing on children who benefit the most. Income transfers have a smaller effect per dollar of government budget on cognitive skill than do child care subsidies, but the effect of income transfers on non-cognitive skill is positive. Therefore, the optimal policy allocates a larger fraction of public funds to income transfers. Finally, in order for income transfers to be effective for improving children's skills, a maternal work requirement is important.

There are several useful directions for future research. First, analyzing single-parent households would be useful. Single-parent households are more likely to suffer from economic hardship and have greater child care demand, compared to two-parent households, so single-parent families may be more responsive to child care subsidies and income transfers. Therefore, the effects on child outcomes and parental behavior might be larger than those found by this study. However, it is worth noting that the fraction of children who live with a single parent is not so large in Australia as in other countries. For example, 16.5% of Australian children at ages 0 to 14 lived with one parent in 2012–13,[102] while Denmark had 29.5% of such children in 2012. The proportions were also greater for the US, the UK, and France (27.2%, 28.2%, and 22.5%, respectively) in 2014 than for Australia.[103]

Second, incorporating saving in the model would be also a useful direction for future study. My model estimates indicate that monetary investment is more productive for cognitive skill development when children are at school age than when they are at preschool age, so parents may save at preschool age and spend the savings for children at school age.

[102] In data from the LSAC, the fraction of children who lived in lone-mother families is smaller at younger ages. There are 11%, 13%, and 14% of children when the children are 0 to 1, 2 to 3, and 4 to 5, respectively.

[103] OECD family database (http://www.oecd.org/els/family/database.htm)

As a result, the effects of child care subsidies and income transfers might be larger if saving is considered.[104]

Third, it would be helpful to model parental resource allocation decisions between multiple children in a family for more accurate evaluations for the effects of child care subsidies and income transfers. In a family with multiple children, parents may have different preferences for each child, so parents may use additional resources due to public assistance for less able children, to compensate the child, or for more able children, because of the child's high productivity.

Forth, introducing fertility decision in the model would be an important direction for future research. Child care subsidy and income transfer programs can affect parents' fertility decisions, and parents might have more children than they would in the absence of public programs. This may result in an increase in government spending because the programs also serve newly born children due to the existence of public programs. Therefore, the program effects per dollar of government expenditure may differ depending on how the public programs affect fertility.

Lastly, I do not have a natural experiment with a comparison group to use as an exogenous source of identification and provide a stronger test of model fit. As discussed in the introduction, one way to compare the effects of child care subsidies and income transfers is to use existing results across studies; however, this is difficult due to differences in outcomes, age groups of children, and program features. Hence, reduced-form studies that analyze child care subsidy and income transfer programs that are directed at preschool age and have similar features would be a useful complement to this study.

[104]Child care subsidies do not provide families with cash that can be saved. However, if child care subsides are provided, parents may work more and have more income to save the additional income for a later investment in children.

Chapter 2: The Effect of Non-Maternal Childcare Time on Children's Cognitive Development

2.1 Introduction

In the US, the labor force participation rate of mothers with children under age 6 rose from 39% in 1975 to 64% in 2014.[105] As a result of the remarkable increase in the labor force participation of mothers over the past several decades, non-maternal childcare has become widely used during early childhood. Baker et al. (2008) documents that the fraction of children under age 6 in the US, who were taken care of by someone other than parents, increased from 37% in 1984 to 56% in 2001. Other reports also show that about 40% to 50% of children under age 6 in the US spend around 25 to 35 hours per week in non-parental childcare.[106] More recently, Laughlin (2013) documents that, in 2011, about 61% of children under age 5 were taken care of by some type of regular childcare and spent an average of 33 hours per week in childcare.[107] These facts imply that many children are exposed to

[105] See US Bureau of Labor Statistics (2015).

[106] See, e.g., Capizzano and Main (2005), Drummond and Seid (2001), National Association of Child Care Resource and Referral Agencies (2011), National Institute of Child Health and Human Development (2006)

[107] Laughlin (2013) includes parental childcare while working or in school as regular childcare arrangements, so the percentage of children who were taken care of by someone other than parents would be smaller than 61%. However, it may not be much smaller because many children had multiple arrangements and there are not many children with parental childcare while working or in school.

non-parental childcare for a large fraction of time during their preschool years. This raises the question of how children are affected by non-parental childcare.

This chapter studies how use of non-maternal childcare affects the development of children's cognitive achievement. This is an important question because cognitive achievement at early ages can affect adult outcomes such as educational attainment, employment and earnings.[108] The process of human development can be described as a dynamic process of skill formation, so skill formed in early childhood serves as an input to a skill formation in the next stage of child development, and as a result affects adult outcomes.[109] Non-maternal childcare is a key input to skill development in early childhood since children spend a large amount of time in non-maternal childcare. Hence, non-maternal childcare could affect adult outcomes through the dynamic process of skill formation.

I estimate the production function for cognitive skill and evaluate the effect of non-maternal childcare time on children's cognitive development, using a sample of children with single mothers from the Child Development Supplement (CDS) of the Panel Study of Income Dynamics (PSID). Children with single mothers are an especially important group because the fraction of this group has risen significantly from 6% in 1950 to 23% in 2005.[110] Moreover, they are likely to experience a disadvantaged family environment. Compared to children with two parents, their mothers are less likely to be college educated, and their family are more likely to be in poverty and receive welfare benefits.[111] Hence,

[108]Many studies have shown that cognitive achievement at early ages is a strong predictor of future outcomes such as educational attainment, employment and earnings. For example, Connolly, Micklewright and Nickell (1992) show that test scores at age 7 have a significant positive association with earnings at age 23. Bernal and Keane (2011) find a significant positive relationship between test scores at age 4 to 6 and educational attainment. See Bernal and Keane (2011) for a detailed review of the literature.

[109]See, e.g., Cunha and Heckman (2008), Cunha et al. (2010), Heckman and Mosso (2014)

[110]See Browning, Chiappori and Weiss (2014).

[111]See Vespa, Lewis and Kreider (2013).

understanding how non-maternal childcare affects the cognitive skill development of those children is important and matters for the design of welfare and childcare policies.

In this study, I show that using a specification that carefully distinguishes non-maternal child care and hours of maternal work is important. Most previous studies have estimated a specification that includes either non-maternal childcare or maternal employment, but not both.[112] However, when estimating the effect of non-maternal childcare, one problem of omitting maternal work is that it conflates the effects of non-maternal childcare and maternal work, but these may have distinct effects. This may be because (1) fatigue or stress from maternal work may cause a negative impact on the quality of maternal childcare, and because (2) working mothers may purchase high quality non-maternal childcare to compensate for reduced quantity and quality of maternal childcare, so it may lead to a positive effect on the quality of non-maternal childcare. Including hours of maternal work, we can distinguish the effect of non-maternal childcare from the effect of maternal work, where the latter can be interpreted as the effect of maternal work through the change in the qualities of maternal and non-maternal childcare. The most important previous study of the effect of non-maternal childcare is Bernal and Keane (2011). They advanced the literature by developing a set of instruments to account for endogeneity of non-maternal childcare.[113] However, they estimate a specification that includes hours of non-maternal childcare, but excludes hours of maternal work.[114] Using instruments similar to theirs, I find

[112]Some studies include both in their models, but they mostly examine the effect of one of them and use the other as a control variable. For example, Desai, Chase-Lansdale and Michael (1989) examine the effect of maternal employment only and include non-maternal childcare as a control variable. They find a negative effect of maternal employment only for boys in high income families.

[113]See Bernal and Keane (2011), Blau and Currie (2006), Lamb (1996), Love, Schochet and Meckstroth (1996) for reviews of the literature.

[114]They are probably unable to incorporate maternal employment and non-maternal childcare use as distinct inputs because they already exploit mother's work history when they impute the measure of non-maternal childcare use.

a positive effect of maternal work, which implies that the beneficial effect from purchasing high quality childcare is larger than the harmful effect from fatigue or stress from work. I also show that omitting hours of maternal work significantly changes the interpretation of the effect of non-maternal childcare. When including hours of work, the negative effect of non-maternal childcare becomes larger by 43%. This is because the effect of maternal work is positive and the correlation between non-maternal childcare and maternal work is positive, so excluding hours of work causes the effect of non-maternal childcare to increase toward zero.

I also show that using a continuous measure of the time spent by a child in non-maternal childcare does not affect the interpretation of the effect of non-maternal childcare, compared to using a discrete measure of non-maternal childcare. Previous studies mostly use the National Longitudinal Survey of Youth (NLSY) data, which provides a more limited measure of non-maternal childcare. The measure available in the NLSY only indicates whether a child was in childcare for at least 10 hours per week, as opposed to actual hours of childcare in the CDS. If we use this limited NLSY measure to estimate the effect of non-maternal childcare, the estimate of the effect could be attenuated because we treat use of non-maternal childcare for less than 10 hours per week as equivalent to no use of non-maternal childcare. To address this issue, Bernal and Keane (2011) make some imputations by using maternal work history.[115] However, the imputations do not fundamentally resolve the problem, and the estimate of the effect of non-maternal childcare could still be attenuated. I test whether using such limited measures for non-maternal childcare attenuate the estimate. To do this, I generate measures that are close to the NLSY measure and the measure of Bernal and

[115]They assign full-time, part-time or no childcare use to each child based on an indicator for non-maternal childcare use and the mother's work history. They also impute childcare use for ages 4 and 5 based on maternal work and the histories of maternal work and childcare until age 3.

Keane (2011), using a continuous measure of non-maternal child care time in CDS of PSID. I estimate the effect of non-maternal childcare by using the same specification of a production function, and find no evidence of the attenuation of the estimate.

One drawback of my study is a small sample size of children with single mothers. The sample size of my study is about a third of the sample size of Bernal and Keane (2011). When a small sample size is too small, we could have less statistical power, so estimates could be imprecise. Nevertheless, the results of my study show that estimates are reasonably precise.

The main findings of this study are sizable negative effects of non-maternal childcare, resulting mainly from use of informal childcare,[116] such as relative, family day care and nanny, at the youngest ages. The preferred estimate indicates that full-time use of informal childcare for the first three years of a child's life (i.e., age 0 to 2) reduces cognitive achievement by 0.559 standard deviations. This predicts a decrease of 0.275 years of schooling. This finding is important because of its implications for the cognitive skill development of young children. Public policy directly or indirectly influences decisions on maternal employment and non-maternal childcare use, and affects the cognitive skill development of young children. A recent report shows that 5.1 million out of 11.4 million children aged 0 to 2 were in informal childcare while only 1.8 million children were in formal childcare.[117] My results imply that providing formal childcare of average quality of current formal childcare could boost cognitive skill by 0.679 standard deviations, compared to using informal childcare. State prekindergarten and Head Start are efforts in this direction, but mainly not directed at young children. Other child care and employment policies, such as EITC and Child Care

[116]Formal childcare includes childcare center, preschool, nursery school, Head Start and pre-kindergarten.

[117]See Laughlin (2013).

and Development Fund (CCDF), do affect young children, but do not encourage to use high quality childcare.

It is also found that children in low income families with working mothers are the most vulnerable group to non-maternal childcare and maternal work. My results indicate that, at the 50th percentile levels of non-maternal childcare time and maternal work time, an additional year of full-time non-maternal childcare use and full-time maternal work reduces cognitive achievement by 0.113 standard deviations if family income is at the 10th percentile, but there is no change in cognitive achievement if family income is at the 75th percentile. This suggests that working mothers in low income families have difficulty finding affordable high quality childcare. It is documented that about 23% of children under age 5 were in families below poverty level.[118] State prekindergarten and Head Start help low income families by providing free high quality childcare. However, Head Start is underfunded and has no employment requirement, so many eligible children in low income families with working mothers could not be enrolled in Head Start.

The rest of this chapter is organized as follows. Section 2.2 develops an estimable specification of the cognitive production function, and describes instruments to be used in analysis. In Section 2.3, the data used in this chapter is described. Section 2.4 presents the estimation results. Lastly, Section 2.5 concludes.

2.2 Specification and Estimation

Following Bernal and Keane (2011), I use a production function framework developed by Leibowitz (1974),[119] which is widely used in the literature on child development. In this

[118]See Laughlin (2013).

[119]Leibowitz (1974) extends the human capital production function framework of Ben-Porath (1967). Todd and Wolpin (2003, 2007) provide good discussions about the general framework for modeling and estimating the cognitive production function.

framework, a child's cognitive ability at ages 5 and above is produced from investments up to age 5. To obtain an estimable production function, the following assumptions are made. First, the arguments of the cognitive production function are maternal childcare time (M), non-maternal childcare time (C) and goods inputs. Mother's hours worked (H) is also included because it can affect the qualities of maternal and non-maternal childcare.[120] These variables are assumed to enter as cumulative from age 0 to 60 months. Second, the functional form of the production function is linear in the cumulative inputs. Third, cumulative family income (G) is used as a proxy for cumulative goods inputs, which is unobservable, so it is implicitly assumed that a fixed fraction of family income is spent on goods for the child's cognitive development and the fraction is the same for all families. Based on these assumptions, the cognitive production function can be written as:

$$A_{ija} = \beta_0 + \beta_1 C_{ij} + \beta_2 M_{ij} + \beta_3 H_{ij} + \beta_4 log G_{ij} + \beta_5 X_{ija} + \epsilon_{ija}, \tag{2.1}$$

where A_{ija} is child i's cognitive achievement in family j at age a ($a = 5, 6, \ldots, 13$), X_{ija} is a vector of child and family characteristics, and ϵ_{ija} is the child's unobserved ability endowment. Equation (2.1) implies that the child's ability after age 5 (or at schooling ages) depends on investments before entering school.

Next, it is assumed that total available time for the child is divided into two types, time with mother (i.e. maternal childcare time) and time in non-maternal childcare. This assumption allows us to substitute total available time minus non-maternal childcare for maternal childcare time, which is unobservable. Then, $M_{ij} = 5T - C_{ijt}$,[121] where T is the

[120]As we will see later, excluding hours of maternal work can cause a biased estimate of the effect of non-maternal childcare.

[121]The relationship between the cumulative maternal childcare and the cumulative non-maternal childcare can be easily derived. Let m_{ijt} and c_{ijt} be maternal childcare time and non-maternal childcare time at age t, respectively. Then, $T = m_{ijt} + c_{ijt}$, so $M_{ij} = \sum_{t=0}^{5} m_{ijt} = \sum_{t=0}^{5}(T - c_{ijt}) = 5T - \sum_{t=0}^{5} c_{ijt} = 5T - C_{ijt}$.

total available time for the child, so the production function can be rewritten as:

$$\begin{aligned} A_{ija} &= (\beta_0 + 5T\beta_2) + (\beta_1 - \beta_2)C_{ij} + \beta_3 H_{ij} + \beta_4 logG_{ij} + \beta_5 X_{ija} + \epsilon_{ija} \\ &= \gamma_0 + \gamma_1 C_{ij} + \beta_3 H_{ij} + \beta_4 logG_{ij} + \beta_5 X_{ija} + \epsilon_{ija}, \end{aligned} \tag{2.2}$$

where $\gamma_0 = \beta_0 + 5T\beta_2$ and $\gamma_1 = \beta_1 - \beta_2$. As seen in (2.2), what we can identify is γ_1, and γ_1 can be interpreted as the effect of non-maternal childcare relative to maternal childcare.

Lastly, a cognitive ability test score (Y_{ija}) measures the child's cognitive ability and has the following measurement process:

$$Y_{ija} = A_{ija} + \mu_{ija}, \tag{2.3}$$

where μ_{ija} is measurement error. Then, the following estimable equation can be obtained:

$$Y_{ija} = \gamma_0 + \gamma_1 C_{ij} + \beta_3 H_{ij} + \beta_4 logG_{ij} + \beta_5 X_{ija} + \tilde{\epsilon}_{ija}, \tag{2.4}$$

where $\tilde{\epsilon}_{ija} = \epsilon_{ija} + \mu_{ija}$.

Many variables are included in X_{ija} to control for child and family characteristics, which may be correlated with the child's unobserved ability endowment or tastes for maternal investment. These include the child's age at the date of assessment, gender and race, birth weight, birth order and whether the child's health was bad at birth or not. For family characteristics, the mother's age and education at the time of child's birth, the presence of siblings aged 0 to 5 and 6 to 17 are included. Birth weight and health status at birth may capture the child's health endowment, which is likely to affect cognitive skills and to be correlated with non-maternal childcare use. Maternal education may measure the mother's human capital or ability. Birth order and the presence of siblings may be correlated with maternal decision on non-maternal childcare use.[122] In the analysis, birth year dummies and birth state dummies are also included to control for unobserved time-varying factors and cross-state factors, respectively, that affect child test scores and are correlated with non-maternal childcare use.

The specification incorporates the mother's hours worked. One reason for this is that excluding this variable may cause a bias when estimating the effect of non-maternal childcare.[123] This is because maternal work time can have an impact on the qualities of maternal and non-maternal childcare. For instance, an increase in maternal work time may cause fatigue and stress, so the quality of maternal childcare may decline due to the fatigue and stress.[124] It is also possible that mothers purchase higher quality non-maternal childcare to compensate for the reduced quantity and quality of maternal childcare because of maternal work. To illustrate this, consider the following simple model:

$$A = A(M \cdot Q_M(H), C \cdot Q_C(H)) \tag{2.5}$$

$$M + C = T \tag{2.6}$$

$$H + M + L = T \tag{2.7}$$

The model shows that the child's cognitive ability is determined by a function of the quantity and quality of maternal childcare (M, Q_M), and the quantity and quality of non-maternal childcare (C, Q_C). The quantity and quality of maternal and non-maternal childcare enter

[122]For example, if a child has a younger sibling, the mother may use non-maternal childcare for the child to take care of the younger child at home. In other words, if a child has a older sibling, the mother may care for the child and the older child may be in non-maternal childcare.

[123]Another reason is that non-maternal childcare and maternal work are correlated as mentioned above.

[124]In the psychology literature, it is claimed that fatigue and stress from long hours of work can lower the quality of mother-child interactions, and so they adversely affect child development (See, e.g., Desai et al., 1989, Hoffman, 1980).

the production function multiplicatively. It is further assumed that the qualities of maternal and non-maternal childcare depend on maternal employment, and that $\frac{\partial Q_M(H)}{\partial H} < 0$ and $\frac{\partial Q_C(H)}{\partial H} > 0$. (2.6) and (2.7) represent the time constraints for the child and mother, respectively, where T is total available time and L is the mother's leisure time.

Given the model above, taking the partial derivative with respect to non-maternal childcare yields the full effect of non-maternal childcare:

$$\begin{aligned}&\frac{\partial A}{\partial(M \cdot Q_M)}\left(Q_M\frac{\partial M}{\partial C} + M\frac{\partial Q_M(H)}{\partial H}\frac{\partial H}{\partial M}\frac{\partial M}{\partial C}\right) + \frac{\partial A}{\partial(C \cdot Q_C)}\left(Q_C + C\frac{\partial Q_C(H)}{\partial H}\frac{\partial H}{\partial M}\frac{\partial M}{\partial C}\right)\\ &= \left(\frac{\partial A}{\partial(C \cdot Q_C)}Q_C - \frac{\partial A}{\partial(M \cdot Q_M)}Q_M\right) - \left(\frac{\partial A}{\partial(M \cdot Q_M)}M\frac{\partial Q_M(H)}{\partial H} + \frac{\partial A}{\partial(C \cdot Q_C)}C\frac{\partial Q_C(H)}{\partial H}\right)\frac{\partial H}{\partial M}\end{aligned} \tag{2.8}$$

The equality can be obtained by substituting $\frac{\partial M}{\partial C} = -1$. As shown in (2.8), the first two terms show the effect of non-maternal childcare relative to maternal childcare (i.e. γ_1 in (2.4)), and we can identify and estimate it if we control for maternal employment. However, if we exclude maternal employment from the regression, then our estimate of the effect of non-maternal childcare could suffer from a bias caused by the last two terms in (2.8). Assuming that $\frac{\partial A}{\partial(M \cdot Q_M)} > 0$ and $\frac{\partial A}{\partial(C \cdot Q_C)} > 0$, the direction of the bias is ambiguous because $\frac{\partial Q_M(H)}{\partial H} < 0$ and $\frac{\partial Q_C(H)}{\partial H} > 0$. Given that $\frac{\partial H}{\partial M}$ is likely to be negative,[125] if the effect of maternal work time through a reduction in the quality of maternal childcare is larger than the effect through an increase in the quality of non-maternal childcare, then there would be a downward bias. If the latter effect is larger, then there would be a upward bias.

It is also interesting to look at the effect of maternal employment since many previous papers in the literature examine it without controlling for non-maternal childcare. We can

[125] Kimmel and Connelly (2007) study mothers' decision of time use, using data from the American Time Use Survey. They jointly estimate a system of four time (paid work, maternal childcare, home production and leisure) demand equations with assumptions that error terms from the four equations are normally distributed and correlated across equations. They report that the estimated correlation between maternal childcare and maternal employment is negative.

derive the full effect of maternal employment as follows:

$$\begin{aligned}
&\frac{\partial A}{\partial(M\cdot Q_M)}\left(Q_M\frac{\partial M}{\partial H}+M\frac{\partial Q_M(H)}{\partial H}\right)+\frac{\partial A}{\partial(C\cdot Q_C)}\left(Q_C\frac{\partial C}{\partial M}\frac{\partial M}{\partial H}+C\frac{\partial Q_C(H)}{\partial H}\right)\\
&=\left(\frac{\partial A}{\partial(M\cdot Q_M)}Q_M-\frac{\partial A}{\partial(C\cdot Q_C)}Q_C\right)\frac{\partial M}{\partial H}+\left(\frac{\partial A}{\partial(M\cdot Q_M)}M\frac{\partial Q_M(H)}{\partial H}+\frac{\partial A}{\partial(C\cdot Q_C)}C\frac{\partial Q_C(H)}{\partial H}\right),
\end{aligned} \tag{2.9}$$

substituting $\frac{\partial C}{\partial M}=-1$. If we control for non-maternal childcare (and so for maternal childcare due to the child's time constraint in (2.6)), then we can estimate the effect of maternal employment that comes through the change in the qualities of maternal and non-maternal childcare, which is the last two terms in the equation above. Hence, β_3 in (2.4) equals $\frac{\partial A}{\partial(M\cdot Q_M)}M\frac{\partial Q_M(H)}{\partial H}+\frac{\partial A}{\partial(C\cdot Q_C)}C\frac{\partial Q_C(H)}{\partial H}$. If non-maternal childcare is not controlled, then the coefficient on maternal employment contains the effect of maternal childcare relative to non-maternal childcare resulting from a reduction of maternal childcare time as well as the effect of maternal employment from the change in the qualities of maternal and non-maternal childcare. The sign of β_3 is ambiguous. If the negative effect of maternal employment through a decline of the quality of maternal childcare is smaller than the positive effect of maternal employment through an increase of the quality of non-maternal childcare, then the estimate of β_3 will be positive. If the former effect is larger than the latter effect, then the estimate will be negative.

Including hours of maternal work enables us to distinguish the effect of non-maternal childcare from the effect of maternal work, but this could result in multicollinearity if hours of non-maternal childcare use and the mother's hours of work are highly correlated. However, the correlation between cumulative hours in non-maternal childcare and cumulative maternal hours worked is about 0.58. When disaggregating non-maternal childcare into formal and informal childcare, the correlations are 0.27 and 0.48, respectively.[126] Hence, the correlations are not extremely high.

The challenge to estimating (2.4) is the endogeneity problem that comes from the correlation between input variables $(C_{ij}, H_{ij}, logG_{ij})$ and the error terms $(\tilde{\epsilon}_{ija})$. As discussed in Bernal and Keane (2011), it is possible that children with high ability are more likely to have mothers with high ability, implying that such mothers tend to work and use non-maternal childcare more. Hence, the least squares estimate of γ_1 would be biased upward. It is also possible that mothers of children with low ability may spend more time on maternal childcare to compensate their children, which implies lower hours of non-maternal childcare and maternal work. This would also cause an upward bias in the least squares estimate of γ_1.

To deal with the endogeneity problem, I use instruments that affect the household's or mother's resources, and so affect maternal investments and the decision of childcare use through the budget and time constraints. The list of instruments can be found in Table 2.1. The first set of instruments is similar to those used by Bernal and Keane (2011).[127] These instruments are constructed by using welfare rules such as time limits for welfare benefits, work requirements and Aid to Families with Dependent Children (AFDC) benefit levels. Before the 1996 Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA), several states were given federal waivers, so they could set their state-level time limits and work requirements as early as the beginning of the 1990's. After the PRWORA was enacted, all states could set their own rules. Thus, the exogenous variation comes from

[126] When using annual hours, the correlations are smaller than when using cumulative hours and decrease as the child ages. For example, the correlation is around 0.55 for children aged 0 or 1, and about 0.26 for 4-year-old children. Similar results can be found when considering cases that mothers ever use non-maternal childcare and ever work for the first five years of their child's life.

[127] See also Fang and Keane (2004) for more details.

Time limits	
	Dummy for whether a state has imposed time limit
	Length of time limit in a state
	Time elapsed since time limit is implemented in a state
	Dummy for whether a mother could have hit time limit[a]
	Potential maximum time left for a mother[a]
	Remaining eligible time left for welfare benefits[a]
	Dummy for whether the child portion of the benefit continues after hitting time limit
Work requirements	
	Dummy for whether a state has implemented work requirement
	Length of time limit before work requirement is in effect
	Time elapsed since work requirement is implemented in a state
	Dummy for whether a work requirement could be in effect for a mother[a]
	Dummy for the existence of age of youngest child exemption
	Age of youngest child exemption
AFDC benefits	
	Real benefits for a family of one parent and one child[b]
	Real benefits for an additional child[b]
EITC	
	Federal and state EITC calculated as described in text
Family leave policy	
	Dummy for whether a state has enacted family leave law
	Maximum length that a mother can take a leave for childbirth
	Time elapsed since the family leave law enacted
	Dummy for whether a mother could have used a leave for childbirth[a]
Wages	
	Average weekly wage of fathers with children age 0 to 5 by state[b]
	Average weekly wage of mothers with children age 0 to 5 by state[b]
	Average hourly wage of childcare workers by state[b]

[a] Individual specific variables, which are functions of youngest or oldest child's age and a policy rule in the state of residence.
[b] Monetary values are adjusted to 2000 dollars using Consumer Price Index from the Bureau of Labor Statistics.

Table 2.1: List of Instruments

the differences in policy changes across states and over time.[128] Some of these instruments are individual specific while others are state specific. For example, a dummy for whether a mother could have hit a welfare time limit is constructed based on the age of the mother's oldest child as well as time limit in the state of her residence. Note that a mother's actual welfare use is not used since it is likely endogenous. AFDC benefit levels differ substantially across states, and change over time.

Another set of instruments is constructed from EITC rules. The substantial expansions of the EITC since the late 1980's provide exogenous variation over time. To calculate federal and state EITC amounts, TAXSIM9 is used.[129] It is assumed that the amount of the EITC is a function of mother's education, the number of children, the state of residence, and tax year. When calculating the EITC, the mean values of wages for 4 education levels (college graduates, some college, high school graduates and high school dropouts) are used. These average wages are computed from the Current Population Survey (CPS), March 1985 - 2003.

The next set of instruments is from family leave regulations. Before 1993, some states had their own family leave laws and provided a job-protected, unpaid maternity leave for women who had maternity-related disability or who needed to care for a newborn.[130] In 1993, the Family and Medical Leave Act (FMLA) was implemented, so a federal-level job-protected, unpaid maternity leave became available for mothers, but some states still have had their own leave provision for mothers separately from the FMLA. Hence, the differences

[128]Major variation is from cross-state heterogeneity in the differences in welfare rules and benefit levels.

[129]TAXSIM9 is a FORTRAN program which enables us to compute tax liabilities and marginal tax rate under federal and state income tax laws by using individual data. See Feenberg and Coutts (1993) and the TAXSIM webpage of the National Bureau of Economic Research (http://www.nber.org/taxsim/) for more information.

[130]Massachusetts enacted maternity leave in 1972, which is the earliest. It was followed by Connecticut, Washington and California. Maine, Minnesota, Oregon, Rhode Island, Tennessee and Wisconsin started their maternity leave provision during the 1980's. See, e.g., Baum (2003), Han, Ruhm and Waldfogel (2009).

in leave provisions across states and over time provide exogenous variation. One variable is at the individual level, which is a dummy for whether a mother could have used a leave for childbirth. This variable is constructed using information on age of the youngest child and the presence of the family leave law.

The last set of instruments includes the average wages of fathers and mothers with children age 0 to 5, and the average wage of childcare workers. These variables reflect the differences in labor market and childcare market conditions across states. They are constructed using data from the CPS, March 1985 - 2003.

Notice that the instruments vary over the child's age from 0 to 5. However, the endogenous variables are cumulative from the child's age 0 to 5, so they are potentially affected by the instruments for all periods from age 0 to 5. For this reason, similar to Bernal and Keane (2011), each endogenous variable is regressed on the instruments for all periods in the first stage regression.

As noted by Bernal and Keane (2011), using many instrument can cause a severe bias of TSLS estimates due to a large number of overidentifying restrictions relative to the sample size.[131] Following Bernal and Keane (2011), a principle components factor analysis with varimax rotation is used to reduce the number of instruments. The factor analysis provides a set of factors that summarizes the correlations of the original variables, and it reduces the number of variables with little loss of information. However, the purpose of the factor analysis for this study is not to find factors that summarize the correlations of the original instruments, but to obtain factors that are highly associated with endogenous variables. Hence, all factors are retained and predicted by the regression scoring method, and then each endogenous variable is regressed on all these factors to select factors by the following

[131]See, e.g., Bekker (1994), Hansen, Hausman and Newey (2008).

criteria. Factors in the first set are selected if the corresponding coefficient is significant at the 1% level in the regression of at least one of the endogenous variables on all factors, and the number of factors in this set is 31. In the second set, 11 factors are selected if the corresponding coefficient is significant at the 1% level in the regression of at least two of the endogenous variables. For factors in the last set, 14 factors whose coefficients are significant at the 5% level in all regressions of the endogenous variables are chosen. These estimated factors are functions of the original instruments, so they are valid instruments given that the original instruments are valid.

Similar to Bernal and Keane (2011), another problem in the model in (2.4) arises from the use of family income as a proxy variable for goods investment. Using a proxy variable can be problematic when interpreting the estimates. For example, γ_1 in (2.4) is interpreted as the effect of non-maternal childcare relative to maternal childcare. However, it is possible that an increase in non-maternal childcare time may induce a change in goods investment, holding family income constant. Since goods investment can affect child development, the estimate of γ_1 can be biased due to the effect of the change in goods investment. An alternative to the use of a proxy is to ignore the goods investment, but this leads to omitted variable bias. Unfortunately, there is no a priori reason to anticipate which approach produce a larger bias.[132]

The quality of non-maternal and maternal childcare is ignored because there is no measure of quality in the CDS. However, the type of non-maternal childcare is observed, so two types of non-maternal childcare (formal and informal childcare) are considered to assess whether the effect of non-maternal childcare differs by type. In this study, formal

[132]See, e.g., Bernal and Keane (2011), Todd and Wolpin (2003, 2007) and Rosenzweig and Schultz (1983) for discussions about this issue.

childcare is defined as non-maternal childcare by trained providers such as a childcare center, preschool, nursery school, Head Start program and pre-kindergarten program. Informal childcare includes care by relatives (e.g., siblings, aunts and grand parents) and non-relatives in the child's home or the provider's home. The effect of non-maternal childcare is also allowed to differ by mother's education because the average childcare quality of more educated mothers may be higher than that of less educated mothers.

The specification in (2.4) ignores inputs at school ages due to the lack of data in the CDS, which is a common problem in the literature on early childhood development. However, the dependent variable in (2.4) is test scores at age 5 to 13, so it could be affected by inputs at these ages, such as school quality. If non-maternal childcare use before school entry is correlated with inputs at school ages, then there may be a omitted variable bias in the estimated effect of non-maternal childcare. The direction of the bias is not obvious, but depends on a correlation between cumulative hours of non-maternal childcare until age 5 and inputs after age 5. A correlation between test scores and inputs at school ages is likely to be positive, so there could be a positive bias if non-maternal childcare until age 5 and inputs after age 5 are positively correlated, or a negative bias if they are negatively correlated. I test the sensitivity to some observed variables at school ages such as log average family income during school ages and whether the child ever attended private school, a special class for gifted children or a special class for disabilities.

In the analysis, I consider interaction effects and non-linear effects. There may be interaction effects between non-maternal childcare, maternal work and family income, so I consider a specification that includes the interaction terms to examine this. The marginal effects of non-maternal childcare and maternal work could diminish as hours of non-maternal childcare and maternal work increase, respectively. The diminishing marginal effects are examined by including squares of non-maternal childcare and maternal work in the main specification.

I also consider unobserved heterogeneity. It is possible that mothers who work/use non-maternal childcare may be different in unobserved ways from those who do not. To test this, three dummies are included in the main specification. The three dummies are (1) D_{ch} which takes the value one if non-maternal childcare is ever used and a mother ever works for the first five years of a child's life, (2) $D_{ch'}$ which takes the value one if non-maternal childcare is ever used and a mother never works, and (3) $D_{c'h}$ takes the value one if non-maternal childcare is never used and a mother ever works. The reference group is, therefore, mothers (or children of mothers) who never use non-maternal childcare and never work. These dummies capture differences between these groups, so they account for the unobserved heterogeneity. If there is no unobserved heterogeneity, then the dummies should have no impact. Each dummy is also interacted with cumulative hours of non-maternal childcare and/or maternal work. This allows the marginal effect of non-maternal childcare for ever working mothers to differ from that for never working mothers, and the marginal effect of maternal work for mothers who ever use non-maternal childcare to differ from that for those who never use non-maternal childcare. The modified specification including dummies is given by:

$$\begin{aligned} Y_{ija} = \gamma_0 + \gamma_0^{ch} D_{ch} + \gamma_0^{ch'} D_{ch'} + \gamma_0^{c'h} D_{c'h} + \gamma_1^{ch} D_{ch} C_{ij} + \gamma_1^{ch'} D_{ch'} C_{ij} \\ + \beta_3^{ch} D_{ch} H_{ij} + \beta_3^{c'h} D_{c'h} H_{ij} + \beta_4 log G_{ij} + \beta_5 X_{ija} + \tilde{\epsilon}_{ija}. \end{aligned} \tag{2.10}$$

The specified models are estimated by two-step GMM as well as TSLS. Two-step GMM generates more efficient estimates than TSLS when a model is over-identified and the assumptions of homoskedasticity and independence are relaxed. The efficiency gain comes from the use of the optimal weighting matrix. The optimal weighting matrix is the inverse of an estimate of the variance-covariance matrix of orthogonality conditions, which is obtained in the first step. In the second step, the GMM estimate is obtained by minimizing the following criterion function: $N\boldsymbol{m}'\boldsymbol{W}\boldsymbol{m}$, where N is the number of observation, $\boldsymbol{m}$ is the vector of the orthogonality conditions and $\boldsymbol{W}$ is a weighting matrix. The optimal weighting matrix from the first step is used for $\boldsymbol{W}$.

2.3 Data

The CDS of the PSID first surveyed 2,394 households of the PSID in 1997 with children under age 13. It collected information on at most two children from each of these households,[133] and it resurveyed these children in 2002/2003 and 2007 if the children were under age 18. The CDS collected information on various dimensions of child development such as cognitive achievement test scores, childcare use, family and school environments, and the child and household characteristics. More information on mothers and households can be obtained from the main PSID surveys. The PSID is a longitudinal survey of a representative sample of individuals and their families which were interviewed annually between 1968 and 1997 and biennially from 1997. The PSID has collected information about each family member, but it has gathered much more details about the head and the spouse. The available information includes employment, income, education, marriage and many other topics.

The sample used in the empirical analysis is children aged 5 to 13 when they took cognitive achievement tests. These children were born in 1984 (age 13 in 1997) to 1997

[133] This is a limitation of the CDS, but the main PSID provides some information about missing siblings such as birth year and age. Therefore, the presence of siblings aged 0 to 5 and the presence of siblings aged 6 to 17 are included in the main specification. In the analysis, a sensitivity check is also conducted using other variables.

(age 5 in 2002 and age 10 in 2007). The sample is restricted to children whose mother was single for 4 years or more, which is not necessarily consecutive, during the period when her child was age 0 to 5. The reason for including some mothers who were married for some periods is to avoid much smaller sample size. The sample includes children who have non-missing data on scores for all three cognitive tests (two tests for children of age 5) in at least one survey year. All three test scores are required to calculate a summary index, which will be used as the main measure for cognitive ability. Since we need information on the work history of the mothers for the first 5 years of the child's life, the sample is further restricted to children who lived with their biological mothers in the same household during that period. After dropping observations with missing data, the final sample is made up of 348 children (490 observations). Some children have two observations if they were between 5 and 13 years old in two consecutive surveys.[134]

The measures of a child's cognitive ability used in the analysis are three standardized test scores which are adjusted by the child's age to make the CDS target child's abilities comparable to national average for children at the same age. The three tests are Letter-Word Identification (LW), Passage Comprehension (PC) and Applied Problems (AP). The first two tests assess children's reading achievement while the last one tests children's math achievement. For each wave of the CDS, the LW and AP were administered to children aged 3 or older, but the PC was used only for children aged 6 or greater. These test scores are renormalized with a mean of zero and a standard deviation of one, and then a summary index of the renormalized test scores is constructed in a similar way to Anderson (2008) and Carneiro and Ginja (2014).[135]

[134]For example, children aged 5 in 1997 are 10 years old in 2002.

[135]The summary index is a weighted average of the three renormalized test scores (for children of age 5, two renormalized test scores since the PC was not conducted for them). See Appendix B.1 for more detail.

Table B.1 shows a descriptive summary of test scores. As shown in the first row of Table B.1, the average value of the summary index is -0.164, so the cognitive achievement of children in the sample is lower than the national average, which is zero by construction. Since test scores are age-standardized, that is, mean zero for each age group, there is no increasing pattern as age increases.

To measure non-maternal childcare time, the retrospective information on all non-maternal childcare arrangements since childbirth is used. The CDS asked the primary caregiver the age in months and/or years (or sometimes in weeks) at which each arrangement started and ended, the type of the arrangement, and how many hours per week the arrangement was used. Using the age at which each arrangement started and ended, we can calculate how many months each arrangement was used. Assuming that a month is equal to 4 weeks, the cumulative non-maternal childcare time of each arrangement is computed by multiplying the number of weeks in the arrangement (i.e. 4 $\times$ the number of months in the arrangement) by the number of hours per week spent in the arrangement.[136]

Table 2.2 shows the rate of non-maternal childcare use and the average cumulative hours of non-maternal childcare. For the first five years of their life, 73.9% of children have an experience of non-maternal childcare, and these children spent, on average, 4,839 hours on non-maternal childcare, which is equivalent to about 2.4 years out of the first 5 years of life. It seems that most mothers did not use non-maternal childcare for the whole 5 years because 42.8% to 54.6% of children were in non-maternal childcare for a given year of the first 5 years. On average, children spent more time in non-maternal childcare as they aged, and the rate of non-maternal childcare use rose as they got older. When considering the type of childcare, informal childcare was always used more than formal childcare except at

[136]There are some inconsistencies in the data, so several assumptions and imputations are made when calculating the cumulative non-maternal childcare time. See Appendix B.2 for more detail.

Age	Non-maternal Childcare Mean	Use Rate	Formal[a] Childcare Mean	Use Rate	Informal[b] Childcare Mean	Use Rate
0 - 60 months	4,839	73.9%	3,068	41.1%	4,170	55.5%
(0 - 4 years)	(3,653)		(2,690)		(3,436)	
0 - 12 months	1,125	42.8%	1,066	6.9%	1,084	37.6%
(0 year)	(650)		(535)		(671)	
12 - 24 months	1,469	47.4%	1,309	11.5%	1,419	38.5%
(1 year)	(805)		(636)		(834)	
24 - 36 months	1,478	50.9%	1,489	15.2%	1,416	37.1%
(2 years)	(806)		(717)		(853)	
36 - 48 months	1,546	53.7%	1,416	26.7%	1,498	30.2%
(3 years)	(814)		(753)		(877)	
48 - 60 months	1,488	54.6%	1,306	33.0%	1,507	25.3%
(4 years)	(988)		(738)		(1,086)	

Note: Means are calculated for non-zero values. Standard deviations are in parentheses.
[a] Formal childcare includes childcare center, preschool, nursery school, Head Start program and pre-kindergarten program
[b] Informal childcare includes care by relatives, non-relatives and self-care.

Table 2.2: Cumulative Hours of Non-Maternal Childcare

age 4. Interestingly, the usage patterns of formal and informal childcare are different from each other. While the rate of formal childcare use shows an increasing trend from 6.9% to 33.0% as children aged, that of informal childcare use decreases from around 38% to 25%.

The number of hours worked by mothers and family income are measured using information from the main PSID. The PSID provides information on annual hours of work and annual total family income. However, the PSID has surveyed respondents biannually since 1997, so there is a missing data problem for children aged 6 to 9 in 2002. In other words, mothers' hours of work and family income are not available in 1998, 2000 and 2002. To fill in the missing years, these two variables are imputed by using the average of the variables in the nearest years (i.e. before and after a year). Family income is adjusted to 2000 dollars using Consumer Price Index from the Bureau of Labor Statistics.

Age	Mean	Employment Rate
0 - 5 years	6,247	89.4%
	(4,155)	
0	1,111	60.3%
	(668)	
1	1,405	60.9%
	(778)	
2	1,325	66.7%
	(776)	
3	1,471	68.7%
	(773)	
4	1,413	73.6%
	(758)	
5	1,443	77.9%
	(764)	

Note: Means are calculated for non-zero values.
Standard deviations are in parentheses.

Table 2.3: Cumulative Mother's Hours of Work

In Table 2.3, the average number of cumulative hours worked by mothers and the maternal employment rate are presented by child's age. The mean cumulative hours of work from age 0 to 5 is 6,247, which is greater than the total cumulative non-maternal childcare time (4,839 hours). This is largely because the information on hours of work was collected based on calendar years. This means that it includes hours of work before the birth of the child and after the child reached age 60 months. As expected, mothers worked more as children aged. The employment rate rises from about 60% in the year of the child's birth, to about 78% when the child is 5 years old.

Comparing Table 2.2 and Table 2.3, it is observed that the employment rate is higher than the rate of non-maternal childcare use, which implies that some mothers work while non-maternal childcare is not used. This is probably because the sample may include mothers who were married for some periods,[137] because some mothers may work while caring for their child, because mother's hours of work was collected based on calendar years while hours of non-maternal childcare based on the child's age in months, or because there exist measurement errors. We also observe that mean hours worked for each year is fairly close to mean hours of non-maternal childcare for a corresponding period.

It would be useful to get an idea of how many mothers work when they use non-maternal childcare, so the number of children by four intervals of hours of maternal work and four intervals of hours of non-maternal childcare at each age is tabulated in Table 2.4. Mothers have a tendency to work when they use non-maternal childcare. For example, for all ages, when non-maternal childcare is used for more than 1,800 hours, the majority of mothers work for more than 1,800 hours, a moderate number of mothers work for 900 to 1,800 hours, and a small number of mothers do not work. When hours of non-maternal childcare is between 900 and 1,800, a large fraction of mothers are working. It is also observed that some mothers work more hours than hours of non-maternal childcare use. The reasons for this may be similar to those for the observation that the employment rate is higher than the rate of non-maternal childcare use.[138]

In Table 2.5, descriptive statistics of control variables used in the analysis are presented. The average cumulative family income from the birth year to the year when the child aged 5 is \$111,955 (or \$18,659 per year) in 2000 dollars. 13.5% of children in the sample are white, and 82.5% are black. The large ratio for black may be because the sample is composed of single mothers.[139] The average birth weight is 111 ounces, and 6.9% of children were

[137]The CDS has information on childcare provided by adults other than parents, so paternal childcare is not included in non-maternal childcare.

[138]In the analysis, the sensitivity to mothers who work more than hours of non-maternal childcare and who work and do not use non-maternal childcare is tested.

[139]The sample used in Bernal and Keane (2011) also had a large ratio for black and hispanic (83%), and they show that this ratio is close to that of all single mothers in the NLSY.

A

	(Hours)	Non-Maternal Childcare (Age 0 - 12 months) 0	> 0 & ≤ 900	> 900 & ≤ 1,800	> 1,800	Total
	0	112 (32.2%)	16 (4.6%)	9 (2.6%)	1 (0.3%)	138 (39.7%)
Mother's Hours of Work (Age 0)	> 0 & ≤ 900	52 (14.9%)	18 (5.2%)	15 (4.3%)	1 (0.3%)	86 (24.7%)
	> 900 & ≤ 1,800	29 (8.3%)	15 (4.3%)	35 (10.1%)	9 (2.6%)	88 (25.3%)
	> 1,800	6 (1.7%)	9 (2.6%)	15 (4.3%)	6 (1.7%)	36 (10.3%)
	Total	199 (57.2%)	58 (16.7%)	74 (21.3%)	17 (4.9%)	348 (100.0%)

B

	(Hours)	Non-Maternal Childcare (Age 12 - 24 months) 0	> 0 & ≤ 900	> 900 & ≤ 1,800	> 1,800	Total
	0	108 (31.0%)	12 (3.4%)	6 (1.7%)	10 (2.9%)	136 (39.1%)
Mother's Hours of Work (Age 1)	> 0 & ≤ 900	38 (10.9%)	12 (3.4%)	3 (0.9%)	9 (2.6%)	62 (17.8%)
	> 900 & ≤ 1,800	22 (6.3%)	15 (4.3%)	12 (3.4%)	20 (5.7%)	69 (19.8%)
	> 1,800	15 (4.3%)	7 (2.0%)	13 (3.7%)	46 (13.2%)	81 (23.3%)
	Total	183 (52.6%)	46 (13.2%)	34 (9.8%)	85 (24.4%)	348 (100.0%)

C

	(Hours)	Non-Maternal Childcare (Age 24 - 36 months) 0	> 0 & ≤ 900	> 900 & ≤ 1,800	> 1,800	Total
	0	88 (25.3%)	15 (4.3%)	3 (0.9%)	10 (2.9%)	116 (33.3%)
Mother's Hours of Work (Age 2)	> 0 & ≤ 900	45 (12.9%)	11 (3.2%)	9 (2.6%)	14 (4.0%)	79 (22.7%)
	> 900 & ≤ 1,800	22 (6.3%)	9 (2.6%)	10 (2.9%)	26 (7.5%)	67 (19.3%)
	> 1,800	16 (4.6%)	14 (4.0%)	14 (4.0%)	42 (12.1%)	86 (24.7%)
	Total	171 (49.1%)	49 (14.1%)	36 (10.3%)	92 (26.4%)	348 (100.0%)

D

	(Hours)	Non-Maternal Childcare (Age 36 - 48 months) 0	> 0 & ≤ 900	> 900 & ≤ 1,800	> 1,800	Total
	0	78 (22.4%)	14 (4.0%)	5 (1.4%)	12 (3.4%)	109 (31.3%)
Mother's Hours of Work (Age 3)	> 0 & ≤ 900	32 (9.2%)	11 (3.2%)	10 (2.9%)	11 (3.2%)	64 (18.4%)
	> 900 & ≤ 1,800	23 (6.6%)	11 (3.2%)	11 (3.2%)	27 (7.8%)	72 (20.7%)
	> 1,800	28 (8.0%)	12 (3.4%)	7 (2.0%)	56 (16.1%)	103 (29.6%)
	Total	161 (46.3%)	48 (13.8%)	33 (9.5%)	106 (30.5%)	348 (100.0%)

E

	(Hours)	Non-Maternal Childcare (Age 48 - 60 months) 0	> 0 & ≤ 900	> 900 & ≤ 1,800	> 1,800	Total
	0	63 (18.1%)	19 (5.5%)	6 (1.7%)	4 (1.1%)	92 (26.4%)
Mother's Hours of Work (Age 4)	> 0 & ≤ 900	30 (8.6%)	15 (4.3%)	13 (3.7%)	18 (5.2%)	76 (21.8%)
	> 900 & ≤ 1,800	34 (9.8%)	9 (2.6%)	10 (2.9%)	22 (6.3%)	75 (21.6%)
	> 1,800	31 (8.9%)	16 (4.6%)	15 (4.3%)	43 (12.4%)	105 (30.2%)
	Total	158 (45.4%)	59 (17.0%)	44 (12.6%)	87 (25.0%)	348 (100.0%)

Note: The information on mother's hours of work was collected based on the calendar years when the child's age is 0, 1, 2, 3, and 4. Hours of non-maternal childcare are based on the five periods of ages, age 0 to 12 months, 12 to 24 months, 24 - 36 months, 36-48 months and 48 to 60 months.

Table 2.4: Number of Children by Cumulative Mother's Hours of Work and Cumulative Hours of Non-Maternal Childcare

Variables	Mean	SD
Cumulative Family Income[a]	111,955	94,146
Boy	0.489	0.501
White	0.135	0.342
Black	0.825	0.381
Birth Weight (Ounces)	110.87	22.36
Birth Order	2.216	1.223
Bad Health at Birth	0.069	0.254
Mother's Age at Child Birth	24.72	5.48
Mother's Years of Schooling at Child Birth	11.81	1.69
Presence of Siblings Aged 5 or Less	0.773	0.420
Presence of Siblings Aged 6 to 17	0.644	0.480

[a] Monetary values are adjusted to 2000 dollars using Consumer Price Index from the Bureau of Labor Statistics.

Table 2.5: Descriptive Statistics of Control Variables

born with bad health. Average mother's age at the child's birth is 24.7, and mothers have, on average, about 12 years of schooling at the time of their child's birth. Almost 77% of children were raised with siblings under age 5 when they were also under age 5, and 64% of children have siblings at schooling ages.

2.4 Results

2.4.1 Overidentification Tests and Explanatory Power of Instruments

The Sargan-Hansen test and the overidentification test for each subset of instruments listed in Table 2.1 are conducted. The results show that we cannot reject the null hypothesis that the instruments have no direct effect on child cognitive achievement.[140] F-tests for joint significance of the instruments in the first stage estimation are also conducted to check the power of the instruments. The results show that the F statistics for endogenous

[140] See Table B.2 in Appendix B.3.

variables are larger than 10, which is the rule of thumb, so the instruments have sufficient explanatory power.[141]

2.4.2 Main Results

In Table 2.6, the estimation results from various alternative methods are reported.[142] For an easier interpretation, the estimates of the effect of cumulative non-maternal childcare and cumulative mother's hours of work are multiplied by 10,000, so we can interpret them as how much the summary index changes when cumulative non-maternal childcare or cumulative mother's hours of work increases by 10,000 hours for the first 5 years of child's life. 10,000 hours for 5 years can be considered as full-time use of non-maternal childcare or full-time work for 5 years because it is equivalent to about 40 hours per week (or 2,000 hours per year), which is close to hours worked by a full-time worker, assuming that the worker allocates her time equally for each of the first 5 years of child's life.

In general, the estimates show a negative effect of non-maternal childcare on children's cognitive achievement. In particular, the GMM estimate implies that a child's cognitive achievement is lower by 0.409 standard deviations when non-maternal childcare is used cumulatively for 10,000 hours (or, equivalently, full-time use of non-maternal childcare for 5 years), holding mother's hours of work and family income constant, and it is statistically significant at the 1% level.[143] This is equivalent to a reduction of 0.082 (= 0.409/5) standard deviations when full-time non-maternal childcare is used for a year. To understand how large this effect is, a similar approach done by Bernal and Keane (2011) is used to link

[141]See Table B.3 in Appendix B.3.

[142]In Appendix B.7, Table B.12 shows the estimation results of all explanatory variables.

[143]The GMM estimate is more negative than the OLS estimate. This suggests that the OLS estimate is biased upward (toward zero) as expected in Section 2.2.

Dependent Variable: Summary Index	OLS (1)	TSLS (2)	GMM (3)	TSLS 31 factors[a] (4)	GMM 31 factors[a] (5)	TSLS 11 factors[b] (6)	GMM 11 factors[b] (7)	TSLS 14 factors[c] (8)	GMM 14 factors[c] (9)
Cumulative Non-Maternal Childcare[d]	-0.196	-0.492**	-0.409***	-0.165	-0.332	-0.255	-0.449	-0.487	-0.415
	(0.150)	(0.196)	(0.116)	(0.393)	(0.349)	(0.709)	(0.698)	(0.503)	(0.490)
Cumulative Mother's Hours of Work[d]	-0.00262	0.346	0.269**	0.282	0.428	1.049	1.080	1.042*	1.061*
	(0.170)	(0.223)	(0.124)	(0.401)	(0.370)	(0.709)	(0.695)	(0.588)	(0.570)
Log Cumulative Family Income	0.185**	0.220*	0.180***	0.299	0.312*	0.0802	0.161	-0.188	-0.232
	(0.0932)	(0.122)	(0.0592)	(0.195)	(0.172)	(0.297)	(0.282)	(0.309)	(0.298)
Mother's Education at Child Birth	0.0601**	0.0460	0.0484**	0.0199	0.00556	-0.0120	-0.0170	0.0373	0.0377
	(0.0289)	(0.0303)	(0.0216)	(0.0368)	(0.0339)	(0.0482)	(0.0473)	(0.0440)	(0.0430)

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The original number of instruments is 134.

[a] Factors whose coefficients are statistically significant at the 1% level in the regression of at least one of endogenous variables.

[b] Factors whose coefficients are statistically significant at the 1% level in the regression of at least two of endogenous variables.

[c] Factors whose coefficients are statistically significant at the 5% level in all regressions of endogenous variables.

[d] These variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.

* $p<0.10$ ** $p<0.05$ *** $p<0.01$

Table 2.6: Estimation Results

cognitive achievement to education attainment.[144] I estimate the relation between children's education (years of schooling) in 2015 and the summary index, and find that an increase in the summary index by one standard deviation is associated with an increase in education by 0.492 years.[145] Based on this result, a drop of 0.082 standard deviations implies a decrease of 0.040 (= 0.082×0.492) years of schooling.[146]

The GMM estimate is obtained by using 134 instruments, so it may be biased toward the OLS estimates due to many instruments. To address this issue, three sets of factors derived from the factor analysis are used as instruments. The estimation results using these factors are reported in columns 5, 7 and 9. The GMM estimates of the effect of non-maternal childcare range from -0.332 to -0.449, all of which are reasonably close to the GMM estimate with the original instruments in column 3, but all are statistically insignificant. This result implies that, when using fewer instruments, estimates are not systematically larger than when using the original instruments. Hence, it seems that many instruments issue is not a problem. The TSLS estimate of the effect of non-maternal childcare in column 2 is -0.492, which is close to the GMM estimate. However, the TSLS estimates with factors are not as closer to the estimate with the original instruments as the GMM estimates with factors.[147] For this reason together with the fact that GMM with the original instruments produces the most precise estimate, the remainder of the chapter will focus on the GMM estimate from using the full set of instruments.

[144] Bernal and Keane (2011) estimate the effect of test scores on highest grade completed, and find that a 1% (or 0.054 standard deviations) increase in test scores is associated with a 0.019 to 0.025 year increase in completed schooling.

[145] See Table B.13 in Appendix B.7 for the estimates.

[146] If we consider a hypothetical world of two types of people: high school graduates (80%) and college graduates (20%), a 0.040 reduction of average years of schooling implies that the percentage of college graduates must decrease by 1% points. This shows a large effect because it is a 5% (= 1%/20%) drop of college graduates.

[147] The TSLS estimates with factors are smaller than that with the original instruments, so this also implies that estimates with fewer instruments are not systematically larger than that with the original instruments.

In Table 2.6, the estimated effects of cumulative mother's hours of work, log cumulative family income and maternal education are also reported. The GMM estimate for mother's hours of work implies an increase of 0.269 standard deviations for full-time maternal work for 5 years, and it is statistically significant. As discussed in Section 2.2, the estimated positive effect of maternal employment implies that the beneficial effect of maternal employment through an increase in non-maternal childcare quality is larger than the harmful effect from a decrease in maternal childcare quality. This suggests that working mothers purchase higher quality non-maternal childcare to compensate for the reduced quantity and quality of maternal childcare due to work.[148] The GMM estimate of the effect of log cumulative family income is 0.180, and it is precise. This implies an increase of 0.125 ($= 0.180 \times \log 2$) standard deviations in cognitive achievement for doubling cumulative family income (i.e., increasing by $\log 2$). For the effect of maternal education, the GMM estimate shows that an additional year of schooling implies an increase of 0.048 standard deviations, and it is statistically significant.

As discussed earlier, omitting maternal employment may cause a bias in the estimate of the effect of non-maternal childcare. To check this, cumulative mother's hours of work is excluded from the model. Column 2 of Table 2.7 shows the GMM estimate of the effect of non-maternal childcare when excluding cumulative mother's hours of work.[149] Comparing with column 1, we find that the estimate falls from -0.409 to -0.286 if maternal employment

[148]Alternative explanation is that, if an increase in maternal employment causes an increase in goods input (For example, working mothers may spend more family income on goods input and less on maternal consumption to compensate for the reduced quantity of maternal childcare due to work.), holding family income constant, then the estimate of the effect of maternal employment may be biased upward. It is also possible that children with higher ability have mothers with higher ability, who are likely to work more and provide a higher quality of maternal childcare. If this is the case, the estimate for maternal employment should become smaller when mother's ability is controlled. This hypothesis is tested by including mother's Passage Comprehension test score in the main specification. Because the test score is not observed for some mothers, a dummy for the missing observation is also included. The result in Table B.14 shows that the estimated effect of mother's hours of work does not become smaller, but larger.

[149]The result for formal and informal childcare is shown in Table B.17.

Dependent Variable: Summary Index	Main Result (1)	Excl. Maternal Employment (2)
Cumulative Non-Maternal Childcare[a]	-0.409***	-0.286***
	(0.116)	(0.105)
Cumulative Mother's Hours of Work[a]	0.269**	
	(0.124)	
Log Cumulative Family Income	0.180***	0.233***
	(0.0592)	(0.0549)

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section **??** are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments.
[a] These variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.
* p<0.10 ** p<0.05 *** p<0.01

Table 2.7: Sensitivity to Omitting Maternal Employment

Dependent Variable: Summary Index				
Cumulative Formal Childcare[a]	Cumulative Informal Childcare[a]	Cumulative Mother's Hours of Work[a]	Log Cumulative Family Income	Mother's Education at Child Birth
-0.232	-0.489***	0.290**	0.174***	0.0421*
(0.173)	(0.130)	(0.125)	(0.0590)	(0.0221)

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments.
[a] These variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.
* p<0.10 ** p<0.05 *** p<0.01

Table 2.8: Type of Non-Maternal Childcare

is omitted. This provides evidence that omitting maternal employment leads to a bias toward zero in the estimate of the effect of non-maternal childcare. As mentioned in the Introduction, many papers do not include maternal employment, so their estimates of the effect of non-maternal childcare may be biased due to the omission of maternal employment.

The effect of non-maternal childcare is likely to differ by the type of non-maternal childcare. This is because trained caregivers may affect children differently from someone

Dependent Variable: Summary Index	Cumulative Non-Maternal Childcare (1)	Cumulative Formal Childcare (2)	Cumulative Informal Childcare (3)
Age 0 to 36 months	-0.796***	0.200	-0.932***
	(0.234)	(0.391)	(0.238)
Age 36 to 60 months	-0.0513	-0.345	0.158
	(0.208)	(0.305)	(0.230)

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments. Cumulative variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.
* p<0.10 ** p<0.05 *** p<0.01

Table 2.9: Effect of Non-Maternal Childcare at Different Ages

who is not trained, such as relatives and babysitters. Table 2.8 reports the estimates for formal and informal childcare. The GMM estimate of the effect of informal childcare is -0.489, and it is significant at the 1% level. This implies a reduction of -0.489 standard deviations in cognitive achievement when full-time informal childcare is used for 5 years. This leads to a decrease of 0.241 ($= 0.489 \times 0.492$) years of schooling. The estimated effect of formal childcare is less than half as large. The GMM estimate indicates a reduction of 0.232 standard deviation for full-time use of formal childcare for 5 years, and it is statistically insignificant. The result here is consistent with Bernal and Keane (2011), who also find a negative effect of informal childcare. Their estimate of the effect of formal childcare is positive, but it is relatively small. Hence, a consensus of this study and Bernal and Keane (2011) is that the negative effect of non-maternal childcare is mainly driven by use of informal childcare.

There may be more critical and sensitive periods for maternal childcare, so non-maternal childcare may harm child cognitive achievement more during these periods. To analyze this, cumulative non-maternal childcare time is disaggregated into two time periods: ages 0 to

36 months and 36 to 60 months.[150] Table 2.9 reports the estimation results from GMM. In column 1, the GMM estimate shows that non-maternal childcare has a large negative impact on children at the youngest ages. The estimate implies that full-time use of non-maternal childcare for the first three years of a child's life reduces cognitive achievement by 0.478 ($= 0.796 \times 3/5$) standard deviations. However, the effect is very small at older ages. The estimate implies a reduction of 0.020 ($= 0.051 \times 2/5$) standard deviations for full-time use of non-maternal childcare for two years (i.e., from age 36 to 60 months). This pattern appears for informal childcare, but not formal childcare. The GMM estimate of the effect of informal childcare at age 0 to 36 months implies a drop of 0.559 ($= 0.932 \times 3/5$) for full-time use of informal childcare from age 0 to 36 months while the estimate for formal childcare implies an increase of 0.120 ($= 0.200 \times 3/5$) standard deviations. This suggests that a child's cognitive skill could be boosted by 0.679 ($= 0.559 + 0.120$) standard deviations if the child were in formal childcare, not in informal childcare, and the increase predicts a rise of 0.334 ($= 0.679 \times 0.492$) years of schooling. Finally, as seen in Section 2.3, when children are very young, a much higher proportion of children are in informal childcare compared to formal childcare. Hence, the result here suggests that the negative impact of non-maternal childcare comes from use of informal childcare when children are very young.

Table 2.10 shows results from a model that allows the effect of non-maternal childcare to vary by maternal education level at the time of child birth, race and gender. In column 1, cumulative childcare variables interact with a dummy for mothers with some college and more education (more than 12 years of schooling). The result shows that non-maternal childcare has more adverse effects for children of more educated mothers. The estimated

[150] Cumulative mother's hours of work and log cumulative family income are also disaggregated into two time periods. However, these variables are collected on a calendar year basis, so the two periods are years when the child aged 0 to 2 and years when the child aged 3 to 5. The results for these variables are shown in Table B.15

Dependent Variable: Summary Index	Mother's Education at Child Birth (1)	Race (2)	Gender (3)
Cumulative Non-Maternal Childcare	-0.361***	-0.577***	-0.678***
	(0.133)	(0.136)	(0.159)
× Some College or More	-0.526*		
	(0.279)		
× White		0.596**	
		(0.252)	
× Boy			0.385
			(0.246)
Cumulative Formal Childcare	-0.309	-0.600***	-0.218
	(0.203)	(0.217)	(0.232)
× Some College or More	0.106		
	(0.448)		
× White		1.119**	
		(0.505)	
× Boy			-0.166
			(0.344)
Cumulative Informal Childcare	-0.395**	-0.653***	-0.962***
	(0.159)	(0.145)	(0.207)
× Some College or More	-1.011***		
	(0.351)		
× White		0.522*	
		(0.278)	
× Boy			0.763**
			(0.318)

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments. Cumulative variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.
* p<0.10 ** p<0.05 *** p<0.01

Table 2.10: Heterogeneity in the Effect of Non-Maternal Childcare

effect of non-maternal childcare from GMM implies that cognitive achievement decreases by 0.887 (= 0.361+0.526) standard deviations for children of mothers with some college degree or more if full-time non-maternal childcare is used for 5 years. On the other hand, cognitive achievement decreases only by 0.361 standard deviations for children of mothers with high school degree or less. The negative effect on children of more educated mothers is much substantial if those children are in informal childcare. The GMM estimate implies a reduction of 1.406 (= 0.395+1.011) standard deviations for full-time use of informal childcare for 5 years. This is a very large impact because it leads to a drop of about 0.692 (= 1.406×0.492) year of schooling. One interpretation for the more negative effect for children of mothers with higher education is that more educated mothers may provide higher quality of maternal childcare (or more valuable time for child development) than less educated mothers. This is consistent with work by Brilli (2017), who shows that the gap between the productivities of maternal childcare and non-parental childcare is greater for high-educated mothers than for low-educated mothers.

In column 2 of Table 2.10, the interactions between cumulative childcare variables and a dummy for whites are all positive and statistically significant. The estimates imply that whites have less or no adverse effect of non-maternal childcare while non-whites have a negative effect. In column 3, cumulative childcare variables are interacted with child's gender. The results imply a larger negative effect for girls.

2.4.3 Extension of the Main Results

Joint Effect of Non-Maternal Childcare, Maternal Work and Earnings

One difficulty for interpreting the estimated effect of non-maternal childcare in Table 2.6 is that it holds mother's hours of work and family income constant. However, mothers

Non-Maternal Childcare		Maternal Employment		Income			
Time (Hours)	Marginal Effect	Time (Hours)	Marginal Effect	Percentiles	Wage[a]	Marginal Effect[b]	Net Effect[c]
2,000	-0.082	0	0		0	0	-0.082
		1,000	0.027	25%	3,618	0.035	-0.020
				50%	5,495	0.053	-0.002
				75%	7,613	0.073	0.019
		2,000	0.054	25%	13,437	0.130	0.102
				50%	17,559	0.169	0.141
				75%	24,807	0.239	0.211

Note: The GMM estimates using the original instruments in Table 2.6 are used.
[a] Wages for 1,000 and 2,000 hours of work are obtained from the wage distribution of mothers who work for 900 to 1,100 hours and for 1,900 to 2,100 hours, respectively.
[b] The marginal effect of income is calculated by $\beta_3 \times \frac{1}{G} \times \Delta Wage$, where average annual family income is used for G.
[c] Net effect is the sum of column 2, 4 and 7.

Table 2.11: Net Effect of Non-Maternal Childcare
under Alternative Assumptions
about Maternal Employment and Wages

can, of course, work while their child is in non-maternal childcare, and they can use their earnings to purchase inputs to the cognitive skill production function. To examine this, the net effect of non-maternal childcare along with changes in mother's hours of work and income from the mother's work is calculated, using the GMM estimates in Table 2.6. The net effect is defined as the sum of the effect of non-maternal childcare, the effect of maternal work and the effect of income from the maternal work. Three cases are considered for an increase of non-maternal childcare by 2,000 hours (or an increase of one year of full-time non-maternal childcare): (1) no change in maternal work time, (2) a 1,000 hour increase in maternal work time, and (3) a 2,000 hour increase in maternal work time. For cases 2 and 3, three different levels (25th percentile, 50th percentile and 75th percentile) of wages are considered. The wages are obtained from the wage distribution of mothers working for 900 to 1,100 hours for case 2, and for 1,900 to 2,100 hours for case 3.

Table 2.11 shows the net effects of a 2,000 hour increase in non-maternal childcare under alternative assumptions about maternal work time and wages. If mother's hours of work do not change, then there is only the effect of non-maternal childcare, so the net effect is the same as the estimated effect of non-maternal childcare that we have seen earlier. If maternal work time increases by 2,000 hours, then the positive effects of maternal employment and income from working outweigh the negative effect of non-maternal childcare for all levels of wages. For example, if the mother's wage is at the median, an increase of 2,000 hours in non-maternal childcare increases the child's cognitive achievement by 0.141 standard deviations. This implies an increase of 0.069 years of schooling. If we compare this case with the case that hours of maternal work do not change, the cognitive achievement of this case is larger by 0.223 (= 0.141 - (- 0.082)) standard deviations than that of no change in hours of maternal work, which implies that working 2,000 hours more induces a 0.110 more years of schooling. If the mother's hours of work increase by 1,000 hours, the net effect is close to zero regardless of the mother's wage.

The exercise here shows that the negative effect of non-maternal childcare is offset or outweighed by the positive effects of maternal work and income from maternal work. Income from maternal work especially plays a large role because the marginal effect of the income is, on average, larger than that of maternal work and it is more than two to three times of the marginal effect of maternal work if wage is at more than the median. This suggests that generating income from maternal employment may be valuable when non-maternal childcare is used. It may be because mothers can purchase higher quality goods or non-maternal childcare by using their earnings.[151]

[151] The net effects of formal and informal childcare along with changes in maternal work time and income from the work are also examined using the estimates in Table 2.8. In Table B.16, we find the same message that the positive effects of mother's hours of work and income from the mother's work at least partially offset the negative effect of non-maternal childcare.

Interaction Effects

Table 2.12 shows the estimation result of the specification with interactions.[152] The results indicate that there is a negative interaction effect between non-maternal childcare and maternal work, and a positive interaction effect between maternal work and family income. The estimates of both interaction effects are statistically significant at the 5% level.[153] Hence, the marginal effect of non-maternal childcare depends on hours of maternal work, and the marginal effect of maternal work differs by hours of non-maternal childcare and log of family income.

To see how the effect of non-maternal childcare differs by hours of maternal work, the marginal effect of non-maternal childcare is calculated at four different hours of maternal work: (1) zero hours, (2) the 25th percentile, (3) the median, and (4) the 75th percentile of cumulative hours of maternal work. Table 2.13 shows the results. It is found that the estimated marginal effect of non-maternal childcare is positive and small when a mother is not working. However, the marginal effect is negative if hours of maternal work is at the 25th, 50th and 75th percentiles, and it is more negative at a larger percentile. For example, if hours of maternal work is at the 25th percentile, full-time use of non-maternal childcare for 5 years reduces a child's cognitive achievement by 0.082 standard deviations, while it does by 0.608 standard deviations if hours of maternal work is at the 75th percentile. These results suggest that non-maternal childcare may not have an harmful impact on children because the estimated marginal effect is not negative for non-working mothers, but it adversely affects children when their mother is working for long hours.

[152] Interaction between cumulative non-maternal childcare and log cumulative family income is excluded because the estimate of the interaction effect is relatively small and statistically insignificant.

[153] The joint significance of the base effect and interaction effects is also tested. For non-maternal childcare, χ^2 statistic is 23.97 and p value is 0.0000. For maternal work, χ^2 statistic is 18.11 and p value is 0.0004.

Dependent Variable: Summary Index	Main Result (1)	Incl. Interactions (2)
Cumulative Non-Maternal Childcare	-0.409***	0.0959
	(0.116)	(0.258)
Cumulative Mother's Hours of Work	0.269**	-3.635**
	(0.124)	(1.642)
Log Cumulative Family Income	0.180***	0.0243
	(0.0592)	(0.0986)
Cumulative Non-Maternal Childcare		-0.709**
× Cumulative Mother's Hours of Work		(0.288)
Cumulative Mother's Hours of Work		0.358**
× Log Cumulative Family Income		(0.142)
Mother's Education at Child Birth	0.0484**	0.0368*
	(0.0216)	(0.0217)

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments. Cumulative non-maternal childcare and mother's hours of work are scaled down by dividing by 10,000, so the estimates of their coefficients are scaled up by 10,000.
* p<0.10 ** p<0.05 *** p<0.01

Table 2.12: Estimation Result with Interaction Effects

Percentiles	Hours of Work	Marginal Effect
-	0	0.096
25%	2,512	-0.082
50%	6,318	-0.352
75%	9,926	-0.608

Note: Estimates in Table 2.12 are used for calculation.

Table 2.13: Marginal Effect of Non-Maternal Childcare at Different Hours of Maternal Work

The marginal effect of maternal work is calculated at four different hours of non-maternal childcare: (1) zero hour, (2) the 25th percentile, (3) the median, and (4) the 75th percentile of cumulative hours of non-maternal childcare; and four different levels of family income: (1) the 10th percentile,[154] (2) the 25th percentile,[155] (3) the median, and (4) the 75th percentile of cumulative family income.[156] In Table 2.14, we find that the marginal effect of maternal work decreases as time in non-maternal childcare increases, holding family income fixed. At the median of family income, the estimated marginal effect of maternal work decreases from 0.447 when non-maternal childcare is not used to 0.163 when hours of non-maternal childcare is at the 50th percentile, and the estimated marginal effect becomes negative (-0.129) when hours of non-maternal childcare is at the 75th percentile. This may be because, given the same family income, purchasing higher quality childcare in order to compensate for the quality reduction of maternal childcare caused by maternal work is harder for mothers who use non-maternal childcare for more hours than for those who use non-maternal childcare for less hours.

The results in Table 2.14 also indicate that children in low income families have a negative effect of maternal work while those in high income families have a positive impact of maternal work. For instance, with the median of hours of non-maternal childcare, full-time maternal work for 5 years reduces cognitive achievement decreases by 0.215 standard deviations if family income is at the 10th percentile, but it increases by 0.351 standard deviations if family income is at the 75th percentile. One explanation for this is that low income families may not be able to purchase higher quality childcare to compensate for

[154] Family income at the 10th percentile is $31,114 in 2000 dollars. According to the 2017 federal poverty guideline for a household size of 2, this is larger than 250% of poverty line ($28,522 in 2000 dollars) and smaller than 300% of poverty line ($34,226 in 2000 dollars).

[155] Family income at the 25th percentile is $46,721 in 2000 dollars. According to the 2017 federal poverty guideline for a household size of 2, this is larger than 400% of poverty line ($45,653 in 2000 dollars).

[156] Logs of these values of family income are used in calculation.

the quality reduction of maternal childcare. This result suggests that it is important for a family to have large enough family income when the mother is working. Otherwise, the positive interaction effect between maternal work and family income cannot offset the negative interaction effect between non-maternal childcare and maternal work and the negative base effect of maternal work (i.e., the effect of maternal work when hours in non-maternal childcare and log cumulative family income are zero). Note that the main result in column 1 of Table 2.12 shows that the estimated effect of maternal work is positive. This positive effect may imply that a majority of families have large enough family income.

The results in this section suggest that a group of children in low income families with working mothers is the most vulnerable group to non-maternal childcare use and maternal work, compared to children in other types of families. This is because they are likely to have negative impacts of both non-maternal childcare and maternal work. For example, suppose that hours of non-maternal childcare and maternal work are at the 50th percentile and consider a 2,000 hour increase in both non-maternal childcare and maternal work. The sum of the estimated effects of non-maternal childcare and maternal work is, then, -0.113 ($= -0.352/5 - 0.215/5$) for the 10th percentile family income, -0.084 ($= -0.352/5 - 0.069/5$) for the 25th percentile family income, -0.037 ($= -0.352/5 + 0.163/5$) for the 50th percentile family income and 0 ($= -0.352/5 + 0.351/5$) for the 75th percentile family income. Moreover, the net effect of non-maternal childcare could be also negative if income from maternal work is not sufficiently large to offset the negative impacts of non-maternal childcare and maternal work. Indeed, at the 10th percentile family income, the estimated net effect is negative (-0.040).[157] Hence, the results here suggest that low income families

[157]The estimated marginal effect of family income is 0.168 ($= 0.0243 + 0.0358 \times \frac{4,000}{10,000}$) at the 50th percentile of hours of maternal work. If we assume the 25th percentile wage (i.e., \$13,437), then the effect of family income is 0.073 ($= 0.168 \times \frac{1}{31,114} \times 13,437$), which is calculated as in Table 2.11.

Percentiles	Hours of Non-Maternal Childcare	Percentiles	Log Family Income[a]	Marginal Effect
-	0	10%	10.35	0.069
25%	1,584			-0.044
50%	4,000			-0.215
75%	8,120			-0.507
-	0	25%	10.75	0.214
25%	1,584			0.102
50%	4,000			-0.069
75%	8,120			-0.362
-	0	50%	11.40	0.447
25%	1,584			0.334
50%	4,000			0.163
75%	8,120			-0.129
-	0	75%	11.93	0.635
25%	1,584			0.523
50%	4,000			0.351
75%	8,120			0.059

Note: Estimates in Table 2.12 are used for calculation.
[a] Logs of the 10th, 25th, 50th and 75th percentile of family income, that is, ln(31,114) = 10.35, ln(46,721) = 10.75, ln(89,450) = 11.40 and ln(151,283) = 11.93, respectively.

Table 2.14: Marginal Effect of Maternal Work at Different Hours of Non-Maternal Childcare and Different Family Income

with working mothers face two difficulties. One is to find affordable high quality non-maternal childcare, and the other is to have enough income to purchase high quality goods to compensate for low quality non-maternal childcare.

Unobserved Heterogeneity

Table 2.15 shows the estimation result of the model in (2.10). It is found that all dummies are small and statistically insignificant, and they are not very different from each other. Thus, the results of this test do not indicate the presence of heterogeneity by "type", where type is defined by the three "ever use/work" indicators. However, the result indicates

Dependent Variable: Summary Index	
D_{ch}	-0.120
	(0.143)
$D_{ch} \times C$	-0.398***
	(0.134)
$D_{ch} \times H$	0.386**
	(0.150)
$D_{ch'}$	-0.130
	(0.216)
$D_{ch'} \times C$	2.177**
	(1.023)
$D_{c'h}$	-0.0630
	(0.135)
$D_{c'h} \times H$	0.267
	(0.235)
$logG$	0.162**
	(0.0663)

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments. Cumulative variables are scaled down by dividing by 10,000, so the estimates of their coefficients are scaled up by 10,000. $D_{ch} = 1$ if non-maternal childcare is ever used and a mother ever works; $D_{ch} = 0$ otherwise. $D_{ch'} = 1$ if non-maternal childcare is ever used and a mother never works; $D_{ch'} = 0$ otherwise. $D_{c'h} = 1$ if non-maternal childcare is never used and a mother ever works; $D_{c'h} = 0$ otherwise. C: cumulative hours of non-maternal childcare, H: cumulative hours of maternal work, $logG$: log cumulative family income.
* p<0.10 ** p<0.05 *** p<0.01

Table 2.15: Estimation Result with Dummies for Non-Maternal Childcare Use and Maternal Employment

a difference in the marginal effect of non-maternal childcare between ever-working and never-working mothers. The estimated marginal effect of non-maternal childcare for ever-working mothers is -0.398 while that for never-working mothers is 2.177, and the hypothesis that the marginal effects of non-maternal childcare for ever-working and never-working mothers are the same is rejected at the 5% significance level ($\chi^2 = 6.11$ and p value = 0.013).[158] This result suggests that the effect of non-maternal childcare relative to maternal childcare differs by work status of mothers. The estimate of the effect is negative for working mothers. This implies that the effect of non-maternal childcare is smaller than that of maternal childcare, so working mothers are more productive than non-maternal childcare. Whereas the positive effect for non-working mothers implies a lower productivity of maternal childcare than non-maternal childcare. The higher productivity of working mothers than non-working mothers may be because working mothers are likely to have higher ability, so they tend to be more productive while non-working mothers are likely to have lower ability, and hence likely to be less productive.

Comparing with the main result, we find that the estimated marginal effects of non-maternal childcare and maternal work for the case of ever using non-maternal childcare and ever working mothers (i.e., $D_{ch} = 1$) are fairly close to those in the main result (main result vs. column 1 of Table 2.15). Moreover, about 70% of children in the sample are in households with ever using non-maternal childcare and ever working mothers. Hence, the adverse effect of non-maternal childcare in the main results may be because many families with single mothers use non-maternal childcare and the mothers work.

	OLS	TSLS	GMM
	(1)	(2)	(3)
Bernal and Keane (2011)[a]	0.021	-0.077*	-0.084**
This Study[b]	-0.073*	-0.156**	-0.207**

[a] Their sample is children whose mothers are single for 5 years after childbirth. They use Peabody Picture Vocabulary Test scores at age 3 to 5 and Peabody Individual Achievement Test scores at age 5 to 6. The number of original instruments is 78. The number of observations is 3,787 (1,464 children).
[b] The sample of this study is children whose mothers are single for at least 4 years during the first 5 years of the child's life. This study uses a summary index of LW test scores at age 5 to 13, PC test scores at age 6 to 13 and AP test scores at age 5 to 13. The number of original instruments is 134. The number of observations is 490 (348 children). Cumulative mother's hours of work, birth year and state dummies are excluded from the model. An interaction of cumulative non-maternal childcare and a dummy for older ages (8 to 13) is included, so the estimate above is for the effect of non-maternal childcare at age 5 to 7.
* p<0.10 ** p<0.05

Table 2.16: Comparison with Bernal and Keane (2011)

Comparison with Bernal and Keane (2011)

It is interesting to compare the results from this study with the results from Bernal and Keane (2011). To compare the results, cumulative mother's hours of work, birth year and state dummies are excluded from the model since Bernal and Keane (2011) do not include them in their model. In addition, Bernal and Keane (2011) use test scores at age 3 to 6, but this study use test scores at age 5 to 13. Because of this, an interaction term between cumulative non-maternal childcare and a dummy for older ages (8 to 13) is included, so the coefficient on cumulative non-maternal childcare can be interpreted as the effect of non-maternal childcare at age 5 to 7. After that, the estimates from both studies are adjusted to be comparable. Bernal and Keane (2011) show that their estimates can be interpreted in terms of a standard deviation of cognitive test scores for a year of full-time childcare use if estimates are multiplied by 4 and then divided by 0.1861, which is the standard deviation

[158] For the marginal effect of maternal work, the marginal effect is 0.386 if non-maternal childcare is ever used while that is 0.267 if non-maternal childcare is never used. However, there is no statistically significant difference between them. $\chi^2 = 0.23$ and p value = 0.634.

of log test scores.[159] The estimates of this study need to be divided by 5 to interpret them as the effect for 2,000 hours spent in non-maternal childcare, which is close to a year of full-time childcare use.

Table 2.16 shows the adjusted estimates of Bernal and Keane (2011)[160] and those of this study. Both studies suggest a common message that non-maternal childcare is harmful for child cognitive development, but it is found that the estimates from this study indicate a larger negative effect of non-maternal childcare. Particularly, the GMM estimate of Bernal and Keane (2011) is only -0.084, but that of this study is -0.207. The smaller estimate of Bernal and Keane (2011) could be because of using a limited measure of non-maternal childcare. When constructing their measure, they treat use of non-maternal childcare for less than 10 hours per week as equivalent to no use of non-maternal childcare, and assign part-time use of non-maternal childcare if a child is in non-maternal childcare at least 10 hours per week and the child's mother is a non-worker or part-time worker. These cases could imply less time in non-maternal childcare and more time with mother than the actual time in non-maternal and maternal childcare, so the estimate of the effect of non-maternal childcare relative to maternal childcare could be attenuated.

I test whether using the limited measure attenuates the estimate of the effect of non-maternal childcare, compared to using a continuous measure. For this test, I convert continuous measures of non-maternal childcare and maternal work in PSID into categorized measures,[161] and then use these to create a measure of non-maternal childcare similar to

[159]See Table 4 and page 483 in Bernal and Keane (2011).

[160]For the original estimates, see Table 6, 8 and 13 in Bernal and Keane (2011)

[161]The NLSY measure of non-maternal childcare is an indicator of using non-maternal childcare at least for 10 hours per week. Using the continuous measure in PSID, I create a similar indicator by assigning a value of one if non-maternal childcare is used larger than 500 hours in a year, and zero otherwise. Bernal and Keane (2011) categorize maternal work into three: non-worker if a mother works for less than 75 hours in a quarter, part-time if a mother works for 75 to 375 hours in a quarter, and full-time if a mother works for more than 375 hours in a quarter. Using annual hours of work in PSID, I create a measure of maternal

Non-Maternal Childcare Measure	Continuous (PSID)[a] (1)	Bernal and Keane (2011)-Like[b] (2)	Binary (NLSY-Like)[c] (3)
Effect of 5 Year Non-Maternal Childcare	-0.286***	-0.338***	-0.288***

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. Cumulative mother's hours of work is excluded in all regressions. The estimation method is two-step GMM with 134 instruments.
[a] Cumulative non-maternal childcare hours
[b] A similar measure to Bernal and Keane (2011) created by categorizing continuous measures in PSID.
[c] A similar measure to the NLSY measure created by categorizing a continuous measure in PSID.
* $p<0.10$ ** $p<0.05$ *** $p<0.01$

Table 2.17: Effect of Using Non-Maternal Childcare for 5 Years by Different Measures

the measure used by Bernal and Keane (2011). A measure similar to the NLSY measure, that indicates whether non-maternal childcare is used for at least 10 hours per week, is also generated. I estimate the effect of non-maternal childcare for each of the three different measures: continuous, Bernal and Keane (2011)-like (BK-like), and NLSY-like, using the same specification that excludes mother's hours of work in (2.4).[162] Table 2.17 shows the result. We find that the estimate of the effect of using non-maternal childcare for 5 years is -0.338 when using the BK-like measure, which is a slightly larger negative impact by -0.052 than when using the continuous measure. When using the NLSY-like measure, the estimate is almost the same as when using the continuous measure. Therefore, we cannot find evidence that using a limited measure, such as BK-like and NLSY-like measures, attenuates the estimate of the effect of non-maternal childcare. This suggests that the difference between this study and Bernal and Keane (2011) shown in Table 2.16 would not be because

work as follows: non-worker if a mother works for less than 300 hours in a year, part-time if a mother works for 300 to 1500 hours in a year, and full-time if a mother works for more than 1500 hours in a year.

[162]Maternal work is excluded because maternal work information is already used when constructing the BK-like measure.

of using different measures of non-maternal childcare, but may be because of other reasons such as using different data and outcome measures.

2.4.4 Non-Linear Effects, and Robustness and Sensitivity of the Results

In Appendix B.4, the nonlinear effects of non-maternal childcare and maternal work are examined. The result of an estimation using a specification that includes squares for non-maternal childcare and maternal work is reported in Table B.4. It is found that the estimates for linear terms for non-maternal childcare and maternal work are negative and the estimates for squares are positive. However, all but the linear for non-maternal childcare are imprecisely estimated. The joint significance test shows that, at the 10% significance level, we cannot reject the hypothesis that coefficients on the two square terms are jointly zero.

In Appendix B.5, the results of various robust and sensitivity tests are reported.[163] Table B.5 shows the results for the sensitivity to various subsets of the original instruments.[164] The negative effect of non-maternal childcare is quite robust to the subsets of the instruments and the estimates using the subsets of the instruments are fairly close to those using the original instruments. The sensitivity to omitting family income is also examined because using family income as a proxy can be a problem as discussed in Section 2.2. As shown in column 2 of Table B.6, excluding log cumulative family income has little impact on the estimated effect of non-maternal childcare.[165] On the other hand, excluding family income causes a substantial increase in the estimated effect of maternal employment. Table B.7 reports the results for the sensitivity to various sets of control variables for siblings. The

[163]In Appendix B.6, the main regression model is estimated using each individual test score and non-cognitive outcomes.

[164]The result for formal and informal childcare is shown in Table B.18.

[165]The result for formal and informal childcare is shown in Table B.17.

estimated effects of non-maternal childcare are close to the estimate using original control variables. The results for the sensitivity to observed variables of inputs during schooling are in Table B.8. The results suggest that omitting inputs at schooling ages may result in a slight downward bias. In Table B.9, the result for the sensitivity to mothers who have more hours of work than hours of non-maternal childcare use and who work while non-maternal childcare is not used is reported. When controlling for such mothers, the estimated effect of non-maternal childcare are close to the estimate from the main result.

2.5 Conclusion

Using the data from the CDS of the PSID, I estimate the effect of non-maternal childcare on child cognitive achievement, and find a negative effect. The negative effect is especially large for informal childcare and for the period when children are very young. It is also found that the positive effects of maternal work and income from the work can offset the negative effect of non-maternal childcare, so maternal work and income from the work may be important. However, it is found that, for low income families, the effect of maternal work is also negative, so the positive effect of family income may not offset the negative effects of non-maternal childcare and maternal work. This suggests that children in low income families with working mothers have the most negative impact, compared to children in other types of families.

The results of this chapter provide important policy implications. First, a more negative effect of informal childcare than formal childcare provides a rationale for policies that incentivize mothers to use formal childcare, such as a child care subsidy, or for childcare program that provide high quality childcare, such as Head Start or universal pre-kindergarten. More importantly, a large negative effect of informal childcare at the youngest ages suggests that a policy aiming to improve child development should focus on the earliest ages and motivate mothers to use less informal childcare when their child is very young. This provides a rationale for providing high quality childcare to very young children in low income families, such as Early Head Start. Lastly, I find that children in low income families with working mothers are the most vulnerable group. One explanation for this is that it may be hard for working mothers in low income families to find affordable high quality non-maternal childcare. This provides an important policy implication, suggesting that child care policy should help such families to use high quality non-maternal childcare, and also a rationale for early intervention programs that promote skills of children in low income families such as Head Start.

Consider the current US child care subsidy policy in the light of the results of this chapter. There are four major child care subsidy programs in the US: the Exclusion for Employer-Provided Dependent Care Expenses (EEPDCE), the Dependent Care Tax Credit (DCTC), Child Care and Development Fund (CCDF) and Head Start. The first two programs are tax subsidies. These programs help working parents to use non-parental childcare, but EEPDCE and DCTC do not encourage parents to use formal (or high quality) childcare. Moreover, low income families are less likely to benefit from EEPDCE and DCTC because low income parents are likely to work for small firms which do not offer EEPDCE or because the parents are likely to have no federal income tax liability. Thus, children in low income families with working mothers are less likely to benefit from EEPDCE and DCTC. CCDF is for low income families who need childcare to work, and its main purpose is to encourage parents with children to work and increase economic self-sufficiency of low income families. However, CCDF does not encourage mothers to use formal (or high quality) childcare. Hence, if the mothers use low quality childcare despite the CCDF benefit, their children would be harmed by non-maternal childcare and maternal work. Lastly, Head Start provides high quality childcare to children in low income families for free if the children are eligible. This program encourages use of formal childcare instead of informal childcare. However, there is no employment requirement and Head Start is underfunded, so many eligible children whose mother is working could not be enrolled in Head Start, and then the children are likely to be in low quality non-maternal childcare. In addition, Head Start is not mainly directed at very young ages (0 to 2 ages), which are the most vulnerable ages to informal childcare.

Despite many interesting results, there are several limitations of this study. First, the quality of childcare is ignored because of the lack of data. However, the quality of childcare could vary even within formal or informal childcare. It is possible that low quality formal childcare has a more adverse effect than average quality maternal childcare, while it has a less adverse effect than low quality maternal childcare. It is also possible that high quality informal childcare has a more positive effect than average quality formal childcare. To deal with this issue, it would be helpful to use variables that measure interactions between child and caregivers or characteristics of non-maternal childcare such as group size, child-staff ratio, and staff's education and experience. To measure the quality of maternal childcare, measures of maternal stress or home environment could be useful. Second, inputs during the schooling period can affect cognitive test scores, but this study ignores them due to data limitations. However, if these omitted inputs are correlated with non-maternal childcare use, then the estimated effect of non-maternal childcare is biased. One way to address this is to use test scores at preschool ages, so we do not worry about the effect of inputs during school ages. If it is not possible, and if only test scores at school ages are available, data on other inputs during school ages would be valuable to estimate the effect of non-maternal childcare. Lastly, this study uses family income as a proxy for goods inputs. Although it may deal with an omitted variable bias, using a proxy variable can cause another bias if changes in hours of non-maternal childcare and maternal work induce change in goods inputs, holding family income fixed. If information on goods investment, such as the number of educational materials and money spent on child, is available, it would be helpful to deal with this issue.

Appendix A: Appendix for Chapter 1

A.1 Functional Forms

A.1.1 Utility Function

$$
\begin{aligned}
u_t &= u_t(x_t, h_{m,t}, \tau_{f,t}, \tau_{fc,t}, \tau_{ic,t}, \theta_{c,t}, \theta_{n,t}; \boldsymbol{X}_t^u, type, \boldsymbol{\varepsilon}_t) \\
&= \frac{x_t}{1,000} + \alpha_{hm,t} h_{m,t} + \alpha_{f,t}\tau_{f,t} + \alpha_{ic,t}\tau_{ic,t} \\
&\quad + \alpha_{c,t}\theta_{c,t} + \alpha_{n,t}\theta_{n,t} + \alpha_{x,hm}\frac{x_t}{1,000} h_{m,t} \\
&\quad + \alpha_x^{sq}\left(\frac{x_t}{1,000}\right)^2 + \alpha_{hm}^{sq} h_{m,t}^2 + \alpha_f^{sq}\tau_{f,t}^2 + \alpha_{ic}^{sq}\tau_{ic,t}^2 + \alpha_c^{sq}\theta_{c,t}^2 + \alpha_n^{sq}\theta_{n,t}^2 \\
&\quad + \alpha_{hh}(h_{m,t} - \tau_{f,t} - \tau_{fc,t} - \tau_{ic,t} \\
&\quad - 30I(t=4,5))I(h_{m,t} > \tau_{f,t} + \tau_{fc,t} + \tau_{ic,t} + 30I(t=4,5))
\end{aligned} \tag{A.1}
$$

$$
\begin{aligned}
\alpha_{j,t} &= \alpha_j^1 + \alpha_j^2 \text{educ}_m + \alpha_j^3 \text{educ}_f + \alpha_j^4 N_t \\
&\qquad + \alpha_j^5 I(t=1) + \alpha_j^6 I(t=2) + \alpha_j^7 I(t=3) + \alpha_j^8 I(type=2) \\
&\qquad + \varepsilon_{j,t}, \quad j \in \{hm, f, ic\} \\
\alpha_{j,t} &= \alpha_j^1 + \varepsilon_{j,t}, \quad j \in \{c, n\}
\end{aligned} \tag{A.2}
$$

A.1.2 Budget Constraint

$$
\begin{aligned}
& x_t + g_t + p_{fc}\tau_{fc,t} + p_{ic}\tau_{ic,t} + TAX_t(h_{m,t}, w_{m,t}, e_{f,t}) \\
& \quad = w_{m,t}h_{m,t} + e_{f,t} \\
& \qquad + CCB_t(p_{fc}, p_{ic}, \tau_{fc,t}, \tau_{ic,t}, h_{m,t}, w_{m,t}, e_{f,t}, t) \\
& \qquad + CCR_t(p_{fc}, \tau_{fc,t}, h_{m,t}, CCB_t) \\
& \qquad + FTB_t(h_{m,t}, w_{m,t}, e_{f,t}, yage_t, N_t) \\
& \qquad + PP_t(h_{m,t}, w_{m,t}, e_{f,t})
\end{aligned} \tag{A.3}
$$

$$
\begin{aligned}
g_t = \pi \Big\{ & w_{m,t}h_{m,t} + e_{f,t} - TAX_t(h_{m,t}, w_{m,t}, e_{f,t}) \\
& + FTB_t(h_{m,t}, w_{m,t}, e_{f,t}, yage_t, N_t) + PP_t(h_{m,t}, w_{m,t}, e_{f,t}) \Big\}
\end{aligned} \tag{A.4}
$$

A.1.3 Time Constraint

$$
\text{Mother: } h_{m,t} + \tau_{m,t} + l_{m,t} = T^p \tag{A.5}
$$

$$
\text{Father: } h_{f,t} + \tau_{f,t} + l_{f,t} = T^p, \quad h_{f,t} = 40 \tag{A.6}
$$

$$
\text{Child: } \tau_{m,t} + \tau_{f,t} + \tau_{fc,t} + \tau_{ic,t} = T^{chd} - 30I(t = 4, 5) \tag{A.7}
$$

A.1.4 Initial skill production function ($r \in \{c, n\}$)

$$\begin{aligned}
\theta_{r,1} &= f_0^r(sex, bw, pb, age_{m,1}, educ_m, emppreg; type, \eta_{r,1}) \\
&= \phi_{r,1} + \phi_{r,2} sex + \phi_{r,3} bw + \phi_{r,4} pb + \phi_{r,5} educ_m \\
&\quad + \phi_{r,6} I(emppreg = 1) + \phi_{r,7} age_{m,1} + \phi_8 I(type = 2) + \eta_{r,1}
\end{aligned} \tag{A.8}$$

A.1.5 Skill Production Function ($r \in \{c, n\}$)

Stage 1: Preschooling Periods ($t = 1, 2, 3$)

$$\begin{aligned}
\theta_{r,t+1} &= f_1^r(\theta_{c,t}, \theta_{n,t}, \tau_{f,t}, \tau_{fc,t}, \tau_{ic,t}, g_t; type, \eta_{r,t+1}) \\
&= \gamma_1^r + \gamma_{c,1}^r \theta_{c,t} + \gamma_{n,1}^r \theta_{n,t} + \gamma_{f,1}^r \tau_{f,t} + \gamma_{fc,1}^r \tau_{fc,t} + \gamma_{ic,1}^r \tau_{ic,t} + \gamma_{e,1}^r g_t \\
&\quad + \gamma_{c,sq,1}^r \theta_{c,t}^2 + \gamma_{n,sq,1}^r \theta_{n,t}^2 + \gamma_{f,sq,1}^r \tau_{f,t}^2 + \gamma_{fc,sq,1}^r \tau_{fc,t}^2 + \gamma_{ic,sq,1}^r \tau_{ic,t}^2 \\
&\quad + \gamma_{e,sq,1}^r g_t^2 + \gamma_{type2,1}^r I(type = 2) + \eta_{r,t+1}
\end{aligned} \tag{A.9}$$

Stage 2: Schooling Periods ($t = 4, 5$)

$$\begin{aligned}
\theta_{r,t+1} &= f_2^r(\theta_{c,t}, \theta_{n,t}, \tau_{f,t}, \tau_{fc,t}, \tau_{ic,t}, g_t, q_t; type, \eta_{r,t+1}) \\
&= \gamma_2^r + \gamma_{c,2}^r \theta_{c,t} + \gamma_{n,2}^r \theta_{n,t} + \gamma_{f,2}^r \tau_{f,t} + \gamma_{fc,2}^r \tau_{fc,t} + \gamma_{ic,2}^r \tau_{ic,t} \\
&\quad + \gamma_{e,2}^r g_t + \gamma_{q,2}^r q_t \\
&\quad + \gamma_{c,sq,2}^r \theta_{c,t}^2 + \gamma_{n,sq,2}^r \theta_{n,t}^2 + \gamma_{f,sq,2}^r \tau_{f,t}^2 + \gamma_{fc,sq,2}^r \tau_{fc,t}^2 + \gamma_{ic,sq,2}^r \tau_{ic,t}^2 \\
&\quad + \gamma_{e,sq,2}^r g_t^2 + \gamma_{q,sq,2}^r q_t^2 + \gamma_{type2,2}^r I(type = 2) + \eta_{r,t+1}
\end{aligned} \tag{A.10}$$

A.1.6 Maternal Wage Function

$$\begin{aligned} lnw_{m,t} &= f^m(age_{m,t}, educ_m, expr_t; type, \varepsilon_{m,t}) \\ &= \mu_{m,1} + \mu_{m,2}\text{age}_{m,t} + \mu_{m,3}\text{age}^2_{m,t} + \mu_{m,4}\text{educ}_m \\ &\quad + \mu_{m,5}\text{expr}_t + \mu_{m,6}\text{expr}^2_t + \mu_{m,7}I(type = 2) + \varepsilon_{m,t} \end{aligned} \tag{A.11}$$

$$expr_{t+1} = expr_t + I(h_{m,t} < 30) + 2I(h_{m,t} \geq 30) \tag{A.12}$$

If work more than or equal to 30 hours per week during pregnancy,

$$expr_1 = age_{m,1} - educ_m - 6 \tag{A.13}$$

If work less than 30 hours per week during pregnancy,

$$expr_1 = age_{m,1} - educ_m - 7 \tag{A.14}$$

If not work during pregnancy,

$$expr_1 = age_{m,1} - educ_m - 8 \tag{A.15}$$

A.1.7 Paternal Earnings Function

$$\begin{aligned} lne_{f,t} &= f^f(age_{f,t}, educ_f; type, \varepsilon_{f,t}) \\ &= \mu_{f,1} + \mu_{f,2}\text{age}_{f,t} + \mu_{f,3}\text{age}^2_{f,t} + \mu_{f,4}\text{educ}_f + \mu_{f,5}I(type = 2) + \varepsilon_{f,t} \end{aligned} \tag{A.16}$$

A.1.8 School Quality Function

$$
\begin{aligned}
q_t &= f^q(educ_m, educ_f; type, \varepsilon_{q,t}) \\
&= \delta_1 + \delta_2 \text{educ}_m + \delta_3 \text{educ}_f + \delta_4 I(type = 2) + \varepsilon_{q,t}
\end{aligned}
\tag{A.17}
$$

A.1.9 Fertility

$$
Pr(N_{t+1} = N_t + 1) = \frac{\exp(\boldsymbol{\rho X}_t^b)}{1 + \exp(\boldsymbol{\rho X}_t^b)} \tag{A.18}
$$

$$
N_{t+1} = N_t + I(\varepsilon_{b,t} < Pr(N_{t+1} = N_t + 1)) \tag{A.19}
$$

$$
\boldsymbol{\rho X}_t^b = \rho_1 + \rho_2 \text{age}_{m,t} + \rho_3 \text{educ}_m + \rho_4 N_t + \rho_5 \text{yage}_t + \rho_6 \text{oage}_t + \rho_7 I(type = 2)
$$

A.1.10 Measurement Equations

$$
m_{c,t} = \theta_{c,t} + \nu_{c,t} \tag{A.20}
$$

$$
m_{n,t} = \theta_{n,t} + \nu_{n,t} \tag{A.21}
$$

$$
m_{q,t} = q_t + \nu_{q,t} \tag{A.22}
$$

A.1.11 Terminal Value

$$
V_6(\Omega_6) = \kappa_1 \log \frac{\hat{x}}{1000} - \kappa_2 \exp(-\bar{\theta}_{c,6}) - \kappa_3 \exp(-\bar{\theta}_{n,6}) \tag{A.23}
$$

A.1.12 Type Distribution

$$Pr(type = j) = \frac{\exp(\boldsymbol{\lambda}_j \boldsymbol{X}^{type})}{1 + \sum_{k=2}^{3} \exp(\boldsymbol{\lambda}_k \boldsymbol{X}^{type})}, \qquad j = 2 \tag{A.24}$$

$$\boldsymbol{\lambda}_j \boldsymbol{X}_t^{type} = \lambda_{j,1} + \lambda_{j,2}\text{educ}_m + \lambda_{j,3}\text{educ}_f + \lambda_{j,4}\text{age}_{m,1} + \lambda_{j,5}\text{age}_{f,1} \tag{A.25}$$

$$+ \lambda_{j,6}N_1 + \lambda_{j,7}\text{oage}_1 + \lambda_{j,8}\text{expr}_1$$

A.2 Policy Functions

A.2.1 Income Tax

$$
\begin{aligned}
&TAX_t(h_{m,t}, w_{m,t}, e_{f,t}) \\
&= \frac{1}{52} \times \begin{cases} 0 & \text{if } E_t \leq E_1^{tax} \\ rate_1^{tax} \times (E_t - E_1^{tax}) & \text{if } E_1^{tax} < E_t \leq E_2^{tax} \\ \{rate_1^{tax} \times (E_2^{tax} - E_1^{tax}) + rate_2^{tax} \times (E_t - E_2^{tax})\} & \text{if } E_2^{tax} < E_t \leq E_3^{tax} \\ \{rate_2^{tax} \times (E_3^{tax} - E_2^{tax}) + rate_3^{tax} \times (E_t - E_3^{tax})\} & \text{if } E_3^{tax} < E_t \leq E_4^{tax} \\ \{rate_3^{tax} \times (E_4^{tax} - E_3^{tax}) + rate_4^{tax} \times (E_t - E_4^{tax})\} & \text{if } E_t > E_4^{tax} \end{cases}
\end{aligned}
\tag{A.26}
$$

where $E_t = 52 \times (h_{m,t}w_{m,t} + e_{f,t})$; E_j^{tax}, $j = 1, \cdots, 4$, is an income cutoff for each income tax bracket; and $rate_j^{tax}$, $j = 1, \cdots, 4$, is a tax rate for each income tax bracket.

A.2.2 Child Care Benefit

$$
\begin{aligned}
&CCB_t(p_{fc}, p_{ic}, \tau_{fc,t}, \tau_{ic,t}, h_{m,t}, w_{m,t}, e_{f,t}, t) \\
&= min\Big\{CCB_t^{formal}(\tau_{fc,t}, h_{m,t}, w_{m,t}, e_{f,t}, t) \\
&\qquad +CCB_t^{informal}(\tau_{ic,t}, h_{m,t}, t),\ p_{fc}\tau_{fc,t} + p_{ic}\tau_{ic,t}\Big\}
\end{aligned}
\tag{A.27}
$$

where CCB_t^{formal} is CCB for formal child care, and $CCB_t^{informal}$ is CCB for informal child care.

$$
\begin{aligned}
&CCB_t^{formal}(\tau_{fc,t}, h_{m,t}, w_{m,t}, e_{f,t}, t) \\
&= \begin{cases} 1.1 \times rate_1^{formal} \times school \times adjustment \times elig\_hrs^{formal} & \text{if } \tau_{fc,t} < 38 \\ rate_2^{formal} \times school \times adjustment \times elig\_hrs^{formal} & \text{if } \tau_{fc,t} \geq 38 \end{cases}
\end{aligned}
\tag{A.28}
$$

$$school = \begin{cases} 1 & \text{if } t = 1, 2, 3 \\ 0.85 & \text{if } t = 4, 5 \end{cases} \tag{A.29}$$

$$adjustment = \begin{cases} 1 & \text{if } E_t \leq E^{ccb} \\ max \left\{ 0,\ 1 - \frac{0.1 \times (E_t - E^{ccb})/52}{rate_3^{formal} \times 50} \right\} & \text{if } E_t > E^{ccb} \end{cases} \tag{A.30}$$

$$elig\_hrs^{formal} = \begin{cases} min(24,\ \tau_{fc,t}) & \text{if } h_{m,t} < 15 \\ \tau_{fc,t} & \text{if } h_{m,t} \geq 15 \end{cases} \tag{A.31}$$

where $rate_1^{formal}$, $rate_2^{formal}$ and $rate_3^{formal}$ are CCB rates for part-time, full-time and 50-hour formal child care, respectively, *school* is a school attendance loading percentage, *adjustment* is a adjustment percentage based on family income, and $elig\_hrs^{formal}$ is eligible formal child care hours.

$$CCB_t^{informal}(\tau_{ic,t}, h_{m,t}, t) = rate^{informal} \times school \times \tau_{ic,t} \times I(h_{m,t} \geq 15) \tag{A.32}$$

where $rate^{informal}$ is a CCB rate for informal child care.

A.2.3 Child Care Rebate

$$\begin{aligned} & CCR_t(p_{fc}, \tau_{fc,t}, h_{m,t}, CCB_t) \\ & \quad = \frac{1}{52} \times min \left\{ ccr_{max},\ percent_{ccr} \times out\text{-}of\text{-}pocket \right\} \times I(h_{m,t} > 0) \end{aligned} \tag{A.33}$$

$$out\text{-}of\text{-}pocket = max \left\{ 0,\ 52 \times (p_{fc}\tau_{fc,t} - CCB_t) \right\} \tag{A.34}$$

where ccr_{max} is the maximum annual limit, $percent_{ccr}$ is a out-of-pocket percentage, and $out\text{-}of\text{-}pocket$ is out-of-pocket expenses for formal child care.

A.2.4 Family Tax Benefit

$$\begin{aligned} &FTB_t(h_{m,t}, w_{m,t}, e_{f,t}, yage_t, N_t) \\ &\qquad = \frac{1}{2} \times \big(FTB_t^A(h_{m,t}, w_{m,t}, e_{f,t}, N_t) + FTB_t^B(h_{m,t}, w_{m,t}, e_{f,t}, yage_t)\big) \end{aligned} \tag{A.35}$$

$$\begin{aligned} &FTB_t^A(h_{m,t}, w_{m,t}, e_{f,t}, N_t) \\ &\qquad = \begin{cases} rate_{max}^{ftb_a} & \text{if } E_t \leq E_{low}^{ftb_a} \\ max\left\{rate_{base}^{ftb_a},\ rate_{max}^{ftb_a} - 0.2 \times (E_t - E_{low}^{ftb_a})\right\} & \text{if } E_{low}^{ftb_a} < E_t \leq E_{up}^{ftb_a}(N_t) \\ max\left\{0,\ rate_{base}^{ftb_a} - 0.3 \times \big(E_t - E_{up}^{ftb_a}(N_t)\big)\right\} & \text{if } E_t > E_{up}^{ftb_a}(N_t) \end{cases} \end{aligned} \tag{A.36}$$

where $rate_{max}^{ftb_a}$ is the maximum rate of FTB Part A; $rate_{base}^{ftb_a}$ is the base rate of FTB Part A; $E_{low}^{ftb_a}$ is a lower income threshold; and $E_{up}^{ftb_a}(N_t)$ is a upper income threshold, which depends on the number of children.

$$\begin{aligned} &FTB_t^B(h_{m,t}, w_{m,t}, e_{f,t}, yage_t) \\ &= I(E_t^{high} \leq E_{ceiling}^{ftb_b}) \times \begin{cases} rate_{max}^{ftb_b}(yage_t) & \text{if } E_t^{low} \leq E^{ftb_b} \\ max\left\{0,\ rate_{max}^{ftb_b}(yage_t) - 0.2(E_t^{low} - E^{ftb_b})\right\} & \text{if } E_t^{low} > E^{ftb_b} \end{cases} \end{aligned} \tag{A.37}$$

where $rate_{max}^{ftb_b}(yage_t)$ is the maximum rate of FTB Part B, which depends on age of the youngest child; $E_t^{high} = max\{h_{m,t}w_{m,t},\ e_{f,t}\}$; $E_t^{low} = min\{h_{m,t}w_{m,t},\ e_{f,t}\}$; $E_{ceiling}^{ftb_b}$ is an income threshold based on earnings of a primary income earner; and E^{ftb_b} is an income threshold based on earnings of a secondary income earner.

A.2.5 Parenting Payment

$$PP_t(h_{m,t}, w_{m,t}, e_{f,t}) = \frac{1}{2} \times I(h_{m,t} \geq h_m^{wr})$$
$$\times \begin{cases} rate_{max}^{pp} & \text{if } e_{f,t} \leq E_f^{pp} \text{ \& } E_t^m \leq E_{m,low}^{pp} \\ rate_{max}^{pp} - rate_1^{pp} \times (E_t^m - E_{m,low}^{pp}) & \text{if } e_{f,t} \leq E_f^{pp} \text{ \& } E_{m,low}^{pp} < E_t^m \leq E_{m,up}^{pp} \\ max\left\{0,\ rate_{max}^{pp} - rate_2^{pp} \times (E_t^m - E_{m,up}^{pp})\right\} & \text{if } e_{f,t} \leq E_f^{pp} \text{ \& } E_t^m > E_{m,up}^{pp} \\ max\left\{0,\ rate_{max}^{pp} - rate_2^{pp} \times (e_{f,t} - E_f^{pp})\right\} & \text{if } e_{f,t} > E_f^{pp} \end{cases} \quad \text{(A.38)}$$

where h_m^{wr} is required hours of maternal work; $rate_{max}^{pp}$ is the maximum rate of PP; $rate_j^{pp}$, $j = 1, 2$, is a reduction rate of PP; $E_t^m = w_{m,t}h_{m,t}$; $E_{m,low}^{pp}$ and $E_{m,up}^{pp}$ are lower and uper income thresholds, respectively, based on mother's earnings; E_f^{pp} is an income threshold based on father's earnings.

A.3 Discretization and Distributions of Choice Variables

A.3.1 Hours of Maternal Work

$$\begin{cases} 0 & \text{if } h_{m,t}^{actual} = 0 \\ 8 & \text{if } 0 < h_{m,t}^{actual} < 15 \\ 20 & \text{if } 15 \leq h_{m,t}^{actual} < 25 \\ 30 & \text{if } 25 \leq h_{m,t}^{actual} < 35 \\ 40 & \text{if } h_{m,t}^{actual} \geq 35 \end{cases} \tag{A.39}$$

A.3.2 Hours of Paternal Child Care

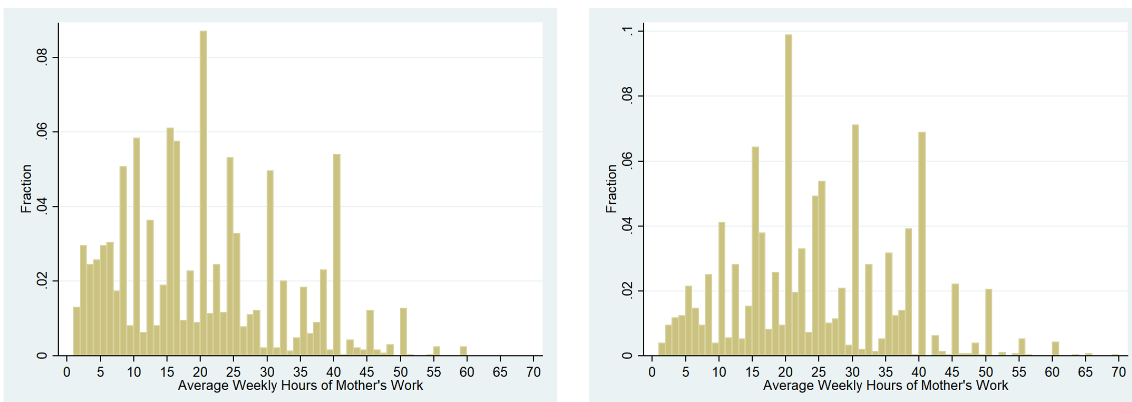
$$\begin{cases} 0 & \text{if } \tau_{f,t}^{actual} = 0 \\ 3 & \text{if } 0 < \tau_{f,t}^{actual} < 5 \\ 7 & \text{if } 5 \leq \tau_{f,t}^{actual} < 10 \\ 12 & \text{if } 10 \leq \tau_{f,t}^{actual} < 20 \\ 26 & \text{if } \tau_{f,t}^{actual} \geq 20 \end{cases} \tag{A.40}$$

A.3.3 Hours of Formal and Informal Child Care ($t = 1, 2, 3$, $j = fc, ic$)

$$\begin{cases} 0 & \text{if } \tau_{j,t}^{actual} = 0 \\ 6 & \text{if } 0 < \tau_{j,t}^{actual} < 10 \\ 14 & \text{if } 10 \leq \tau_{j,t}^{actual} < 20 \\ 24 & \text{if } 20 \leq \tau_{j,t}^{actual} < 30 \\ 38 & \text{if } \tau_{j,t}^{actual} \geq 30 \end{cases} \tag{A.41}$$

A.3.4 Hours of Formal and Informal Child Care ($t = 4, 5,\ j = fc, ic$)

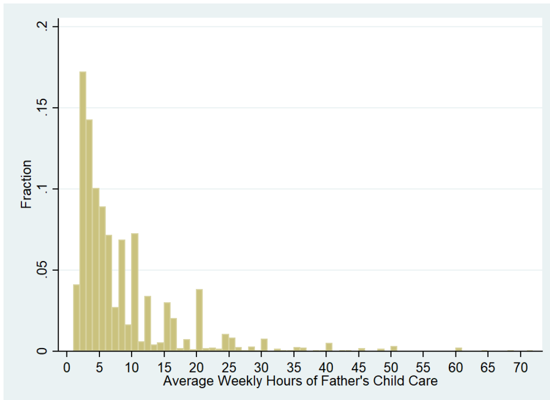
$$\begin{cases} 0 & \text{if } \tau_{j,t}^{actual} = 0 \\ 3 & \text{if } 0 < \tau_{j,t}^{actual} < 5 \\ 7 & \text{if } 5 \leq \tau_{j,t}^{actual} < 10 \\ 12 & \text{if } 10 \leq \tau_{j,t}^{actual} < 15 \\ 20 & \text{if } \tau_{j,t}^{actual} \geq 15 \end{cases} \tag{A.42}$$



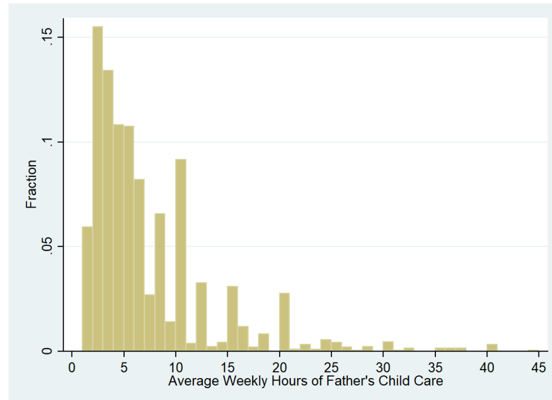
(a) Preschool Periods

(b) School Periods

Figure A.1: Hours of Maternal Work

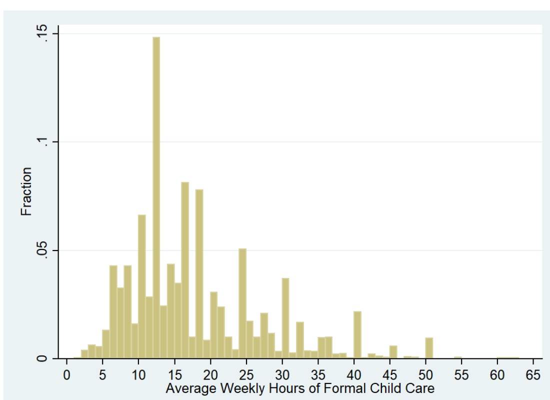


(a) Preschool Periods

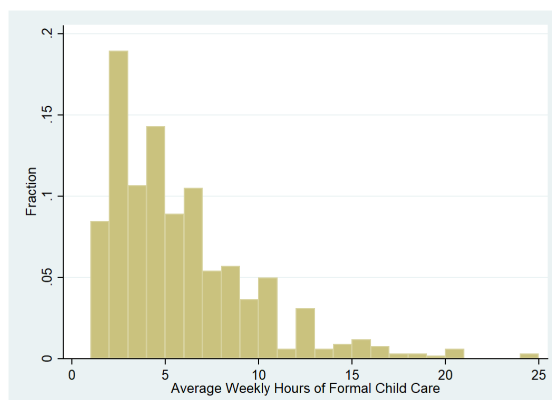


(b) School Periods

Figure A.2: Hours of Paternal Child Care

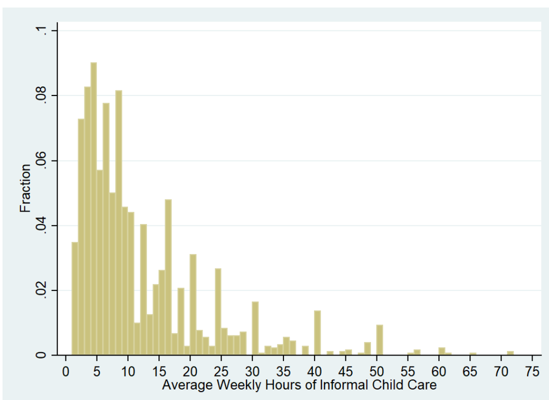


(a) Preschool Periods

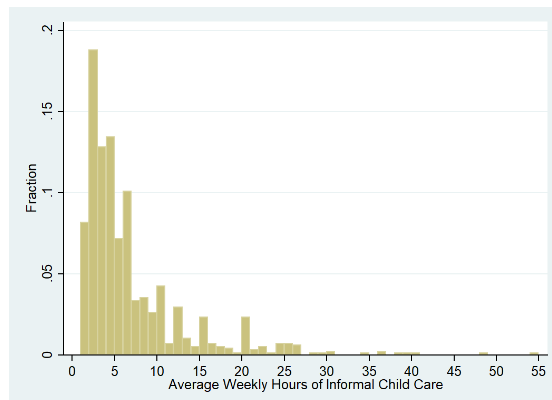


(b) School Periods

Figure A.3: Hours of Formal Child Care



(a) Preschool Periods



(b) School Periods

Figure A.4: Hours of Informal Child Care

A.4 Descriptive Statistics

Boy	52.8%
Prematrue Birth	6.1%
Child's Birth Weight (kg)	3.45
	(0.56)
Maternal Age at t=1	32.1
	(4.57)
Paternal Age at t=1	34.4
	(5.49)
Maternal Employment During Pregnancy	69.6%

	Period	
	Preschool	School
Number of Children	2.25	2.67
	(0.99)	(0.98)
Age of the Youngest	1.47	5.28
	(1.52)	(2.37)
Age of the Oldest	5.02	10.02
	(3.97)	(3.75)
Maternal Work Experience	11.99	14.00
	(4.74)	(5.19)
Maternal Hourly Wage	39.99	37.94
	(44.38)	(45.86)
Paternal Weekly Earnings	1786	1828
	(1323)	(1389)

Maternal Education		Paternal Education	
Less than Year 12	10.3%	Less than Year 12	10.4%
Year 12 or equivalent	14.7%	Year 12 or equivalent	10.0%
Certificate	22.8%	Certificate	35.7%
Advanced Diploma/Diploma	10.5%	Advanced Diploma/Diploma	9.1%
Bachelor Degree	25.0%	Bachelor Degree	19.9%
Graduate Diploma/Certificate	7.9%	Graduate Diploma/Certificate	6.4%
Postgraduate Degree	8.9%	Postgraduate Degree	8.4%
Average Years of Schooling	13.8	Average Years of Schooling	13.6
	(1.9)		(1.9)

Note: Standard deviations are in parentheses. Monetary values are adjusted to 2012 Australian dollars. The average exchange rate in 2012 was 1 AUD = 1.0356 USD.

Table A.1: Descriptive Statistics

A.5 Measures of Skills

Measure	Observations					
	Ages 0 to 1	2 to 3	4 to 5	6 to 7	8 to 9	10 to 11
PEDS: concern about general development	2,102					
PEDS: concern about speech	2,101	2,068	2,101	2,088		
PEDS: concern about understand speech	2,090	2,060	2,101	2,088		
PEDS: concern about use of hands	2,100	2,062				
PEDS: concern about gross motor	2,101	2,066				
CSBS: speech (use of sound and words)	1,811					
CSBS: symbolic (understanding of words and use of objects)	1,806					
Communication Skill Scale		1,803				
MCDI: vocabulary		1,777				
MCDI: grammartical markers		1,757				
Reading competencies index			2,102			
PPVT score			2,065	2,083	2,077	
WAI score			2,040			
Communication Skill Index			2,101			
CCC: speech scaled score				2,086		
CCC: syntax scaled score				2,086		
CCC: semantics scaled score				2,084		
CCC: coherence scaled score				2,086		
Matrix reasoning score				2,082	2,071	1,885
Reading progress (mother)				2,080	2,086	1,934
Math progress (mother)				2,041	2,085	1,936
Overall school achievement (mother)				2,092	2,097	1,949
Reading progress (teacher)				1,738	1,826	1,637
Math progress (teacher)				1,737	1,821	1,616
Overall school achievement (teacher)				1,733	1,821	1,631
ARS: language and literacy (teacher)				1,743	1,828	1,648
ARS: math thinking (teacher)				1,737	1,820	1,626

Table A.2: Cognitive Skill Measures

Measure	Observations					
	Ages 0 to 1	2 to 3	4 to 5	6 to 7	8 to 9	10 to 11
CSBS: social (emotion, use of eye gaze, communication and gesture)	1,812					
Degree of positive response	2,080	2,061	2,084	2,086	2,077	
Degree of negative response	2,081	2,061	2,083	2,089	2,077	
Degree of fear towards interviewer	2,073					
Degree of shy/anxiety			2,083	2,085	2,078	
Approach scale	1,910	1,805				
Irritability scale	1,910					
Cooperativeness scale	1,910					
Persistence scale		1,804	1,918	2,088		
Reactivity scale		1,802	1,918	2,088		
Socialability scale			1,918	2,088		
Social emotional problems scale				2,064	2,070	
BITSEA: problems scale		2,069				
BITSEA: competence scale (mother)		2,068				
BITSEA: competence scale (father)		1,750				
PEDS: emotional functioning		1,800	1,916	2,088	2,084	1,926
PEDS: social functiong		1,788	1,911	2,086	2,083	1,921
SDQ: prosociality scale (mother)			1,918	2,089	2,084	1,926
SDQ: hyperactivity scale (mother)			1,917	2,089	2,084	1,926
SDQ: emotional scale (mother)			1,918	2,089	2,084	1,926
SDQ: peer problems scale (mother)			1,918	2,089	2,084	1,926
SDQ: conduct problems scale (mother)			1,918	2,089	2,084	1,926
SDQ: prosociality scale (teacher)				1,744	1,833	1,647
SDQ: hyperactivity scale (teacher)				1,745	1,834	1,646
SDQ: emotional scale (teacher)				1,745	1,834	1,645
SDQ: peer problems scale (teacher)				1,745	1,834	1,645
SDQ: conduct problems scale (teacher)				1,744	1,834	1,646
SDQ: prosociality scale (child)						1,878
SDQ: hyperactivity scale (child)						1,879
SDQ: emotional scale (child)						1,879
SDQ: peer problems scale (child)						1,879
SDQ: conduct problems scale (child)						1,879
Approach to learning				1,741	1,834	1,648
SATI: introversion					2,084	1,926
SATI: persistence					2,084	1,925
SATI: reactivity					2,084	1,926
Marsh: peer relations scale					2,072	1,882
Marsh: general self-perception scale					2,072	1,879
SSIS: self-control scale						1,926

Table A.3: Non-Cognitive Skill Measures

A.6 Parameter Estimates

Skill Production Function					
Initial Skills					
Cog. Skill			Non-Cog. Skill		
$\phi_{c,1}$	-0.5536	(0.3550)	$\phi_{n,1}$	0.3954	(0.2572)
$\phi_{c,2}$	-0.0798	(0.0593)	$\phi_{n,2}$	0.0151	(0.0400)
$\phi_{c,3}$	0.1048	(0.0412)	$\phi_{n,3}$	-0.0669	(0.0259)
$\phi_{c,4}$	-0.3720	(0.1050)	$\phi_{n,4}$	-0.0244	(0.0964)
$\phi_{c,5}$	0.0445	(0.0132)	$\phi_{n,5}$	0.0230	(0.0142)
$\phi_{c,6}$	0.0132	(0.0500)	$\phi_{n,6}$	0.3954	(0.0798)
$\phi_{c,7}$	-0.0171	(0.0086)	$\phi_{n,7}$	-0.0229	(0.0070)
$\phi_{c,8}$	0.6823	(0.0904)	$\phi_{n,8}$	0.0661	(0.1277)
Preschool Age					
Cog. Skill			Non-Cog. Skill		
γ_1^c	-0.3729	(0.0337)	γ_1^n	-0.1804	(0.0454)
$\gamma_{c,1}^c$	0.2607	(0.0191)	$\gamma_{c,1}^n$	0.0106	(0.0185)
$\gamma_{n,1}^c$	0.1493	(0.0167)	$\gamma_{n,1}^n$	0.5409	(0.0138)
$\gamma_{f,1}^c$	0.0032	(0.0008)	$\gamma_{f,1}^n$	-0.0003	(0.0002)
$\gamma_{fc,1}^c$	0.0080	(0.0003)	$\gamma_{fc,1}^n$	-0.0037	(0.0003)
$\gamma_{ic,1}^c$	-0.0028	(0.0003)	$\gamma_{ic,1}^n$	-0.0027	(0.0007)
$\gamma_{e,1}^c$	0.0029	(0.0007)	$\gamma_{e,1}^n$	0.0070	(0.0022)
$\gamma_{f,sq,1}^c$	-0.000008	(0.000171)	$\gamma_{f,sq,1}^n$	-0.000026	(0.000024)
$\gamma_{fc,sq,1}^c$	-0.000187	(0.000008)	$\gamma_{fc,sq,1}^n$	-0.000001	(0.000001)
$\gamma_{ic,sq,1}^c$	-0.000011	(0.000008)	$\gamma_{ic,sq,1}^n$	-0.000002	(0.000099)
$\gamma_{e,sq,1}^c$	-0.000033	(0.000031)	$\gamma_{e,sq,1}^n$	-0.000010	(0.000009)
$\gamma_{type,1}^c$	0.9330	(0.0407)	$\gamma_{type,1}^n$	0.2104	(0.0652)
School Age					
Cog. Skill			Non-Cog. Skill		
γ_2^c	-0.1605	(0.0159)	γ_2^n	-0.0876	(0.0150)
$\gamma_{c,2}^c$	0.6730	(0.0091)	$\gamma_{c,2}^n$	0.0521	(0.0207)
$\gamma_{n,2}^c$	0.0469	(0.0076)	$\gamma_{n,2}^n$	0.5717	(0.0127)
$\gamma_{f,2}^c$	0.0013	(0.0003)	$\gamma_{f,2}^n$	0.0005	(0.0007)
$\gamma_{fc,2}^c$	0.0004	(0.0001)	$\gamma_{fc,2}^n$	-0.0037	(0.0005)
$\gamma_{ic,2}^c$	-0.0024	(0.0004)	$\gamma_{ic,2}^n$	-0.0023	(0.0011)
$\gamma_{e,2}^c$	0.0099	(0.0017)	$\gamma_{e,2}^n$	0.0062	(0.0027)
$\gamma_{q,2}^c$	0.3771	(0.0348)	$\gamma_{q,2}^n$	0.1990	(0.0998)
$\gamma_{f,sq,2}^c$	-0.000058	(0.000016)	$\gamma_{f,sq,2}^n$	-0.000014	(0.000264)
$\gamma_{fc,sq,2}^c$	-0.000110	(0.000011)	$\gamma_{fc,sq,2}^n$	-0.000012	(0.000020)
$\gamma_{ic,sq,2}^c$	-0.000044	(0.000010)	$\gamma_{ic,sq,2}^n$	-0.000027	(0.000027)
$\gamma_{e,sq,2}^c$	-0.000040	(0.000008)	$\gamma_{e,sq,2}^n$	-0.000079	(0.000060)
$\gamma_{q,sq,2}^c$	-0.002714	(0.194765)	$\gamma_{q,sq,2}^n$	-0.006361	(0.386725)
$\gamma_{type,2}^c$	-0.0508	(0.0107)	$\gamma_{type,2}^n$	0.0535	(0.0419)
Productivity Shocks			Measurement Errors		
σ_{η_c}	0.6225	(0.0120)	σ_{ν_c}	0.1859	(0.0197)
σ_{η_n}	0.7690	(0.0116)	σ_{ν_n}	0.1074	(0.0528)

Note: Standard errors are in parentheses.

Table A.4: Parameter Estimates

Utility Function

Maternal Hours of Work		
α_{hm}^1	0.01882	(0.00259)
α_{hm}^2	0.00607	(0.00021)
α_{hm}^3	0.00309	(0.00038)
α_{hm}^4	-0.01759	(0.00059)
α_{hm}^5	-0.15044	(0.00321)
α_{hm}^6	-0.06559	(0.00404)
α_{hm}^7	-0.03202	(0.00388)
α_{hm}^8	0.00747	(0.00172)
α_{hm}^{sq}	-0.00356	(0.00009)

Paternal Child Care		
α_f^1	0.00290	(0.00052)
α_f^2	0.00058	(0.00007)
α_f^3	0.00003	(0.00002)
α_f^4	-0.00094	(0.00029)
α_f^5	-0.01199	(0.00149)
α_f^6	-0.01430	(0.00220)
α_f^7	-0.01392	(0.00150)
α_f^8	-0.00227	(0.00114)
α_f^{sq}	-0.00448	(0.00011)

Informal Child Care		
α_{ic}^1	-0.00130	(0.00058)
α_{ic}^2	-0.00008	(0.00004)
α_{ic}^3	-0.00021	(0.00006)
α_{ic}^4	-0.00198	(0.00037)
α_{ic}^5	-0.00020	(0.00019)
α_{ic}^6	0.00731	(0.00181)
α_{ic}^7	0.01471	(0.00150)
α_{ic}^8	0.00192	(0.00063)
α_{ic}^{sq}	-0.00188	(0.00006)

Cog. Skill		
α_c^1	0.04016	(0.01964)
α_c^{sq}	-0.00499	(0.35952)

Non-Cog. Skill		
α_n^1	0.51653	(0.03609)
α_n^{sq}	-0.03696	(0.01322)

Others		
α_x^{sq}	-0.06062	(0.00586)
$\alpha_{x,hm}$	-0.00713	(0.00098)
α_{hh}	-0.00838	(0.00025)

Budget Constraint		
p_{fc}	7.99	(0.4640)
p_{ic}	2.61	(1.1265)
π	0.126	(0.0248)

Terminal Value Function		
κ_1	0.2539	(0.1932)
κ_2	3.1594	(0.2257)
κ_3	0.6003	(0.0742)

Preference Shocks		
$\sigma_{\varepsilon_{hm}}$	0.1340	(0.0019)
σ_{ε_f}	0.0590	(0.0014)
$\sigma_{\varepsilon_{ic}}$	0.0319	(0.0006)
σ_{ε_c}	0.6272	(0.1996)
σ_{ε_n}	0.3827	(0.1923)

Maternal Wage		
$\mu_{m,1}$	1.7222	(0.1330)
$\mu_{m,2}$	-0.0160	(0.0027)
$\mu_{m,3}$	-0.0004	(0.0001)
$\mu_{m,4}$	0.1168	(0.0074)
$\mu_{m,5}$	0.0848	(0.0038)
$\mu_{m,6}$	-0.0011	(0.0001)
$\mu_{m,7}$	0.7542	(0.0539)

Paternal Earnings		
$\mu_{f,1}$	4.6322	(0.0536)
$\mu_{f,2}$	0.0638	(0.0025)
$\mu_{f,3}$	-0.0008	(0.00002)
$\mu_{f,4}$	0.1041	(0.0018)
$\mu_{f,5}$	0.1441	(0.0162)

Scholl Quality		
δ_1	-1.8674	(0.0500)
δ_2	0.0707	(0.0074)
δ_3	0.0519	(0.0072)
δ_4	0.3151	(0.0703)

Fertility		
ρ_1	4.4531	(0.1931)
ρ_2	-0.0099	(0.0030)
ρ_3	-0.0961	(0.0198)
ρ_4	-0.6135	(0.1133)
ρ_5	1.1459	(0.0727)
ρ_6	-1.3736	(0.0299)
ρ_7	1.3403	(0.1150)

Wage or Earnings Shocks		
σ_{ε_m}	0.3410	(0.0275)
σ_{ε_f}	0.3487	(0.0129)

School Quality Shock		
σ_{ε_q}	0.1660	(0.0515)

School Quality Measurement Errors		
σ_{ν_q}	0.7810	(0.0136)

Type Distribution		
$\lambda_{2,1}$	-4.1410	(0.0587)
$\lambda_{2,2}$	0.1065	(0.0121)
$\lambda_{2,3}$	0.1030	(0.0204)
$\lambda_{2,4}$	0.0666	(0.0099)
$\lambda_{2,5}$	-0.0199	(0.0015)
$\lambda_{2,6}$	-0.7845	(0.0410)
$\lambda_{2,7}$	0.0502	(0.0103)
$\lambda_{2,8}$	0.0292	(0.0036)

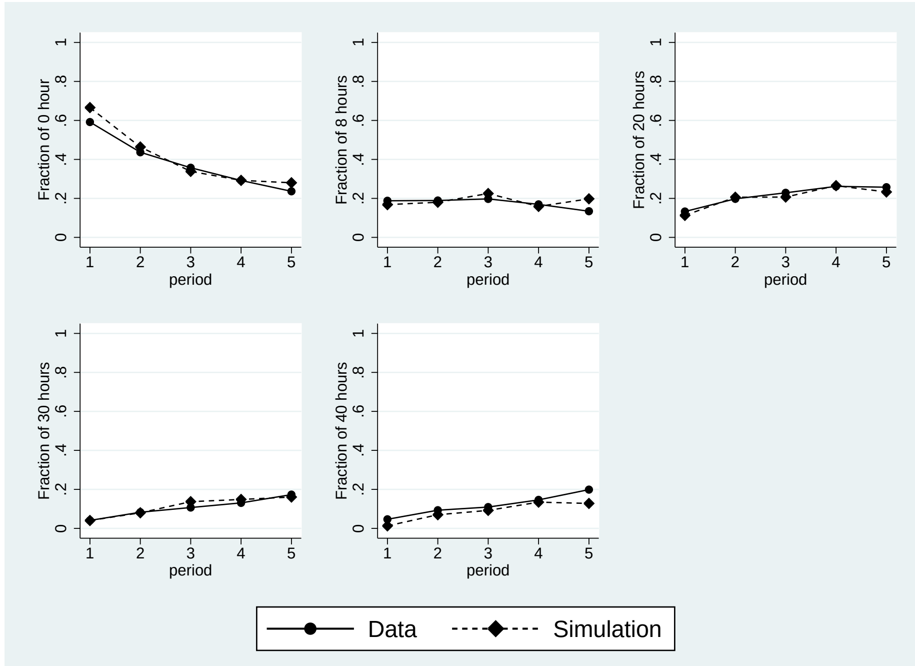
Note: Standard errors are in parentheses.

Table A.5: Parameter Estimates

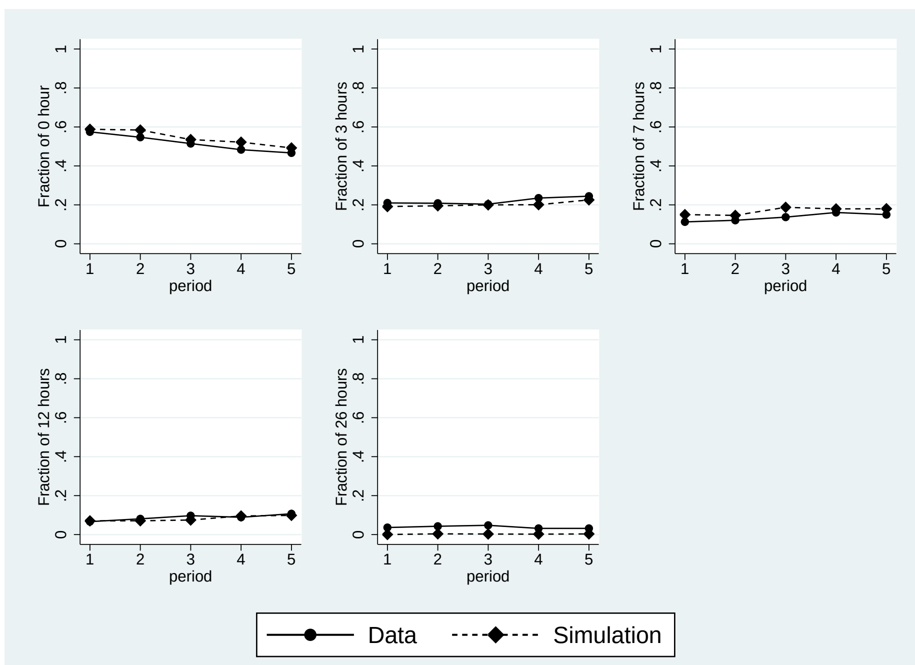
A.7 Model Fit

	Preschool		School	
	Data	Simulation	Data	Simulation
# of Children	2.25	2.29	2.67	2.65
Work Experience	11.99	11.90	14.00	13.87
Maternal Hourly Wage	39.99	36.56	37.94	32.71
Paternal Weekly Earnings	1786	1640	1828	1645
Cognitive Skill	0.000	-0.007	0.000	0.029
Non-Cognitive Skill	0.000	0.020	0.000	-0.015
School Quality			0.000	-0.098

Table A.6: Model Fit

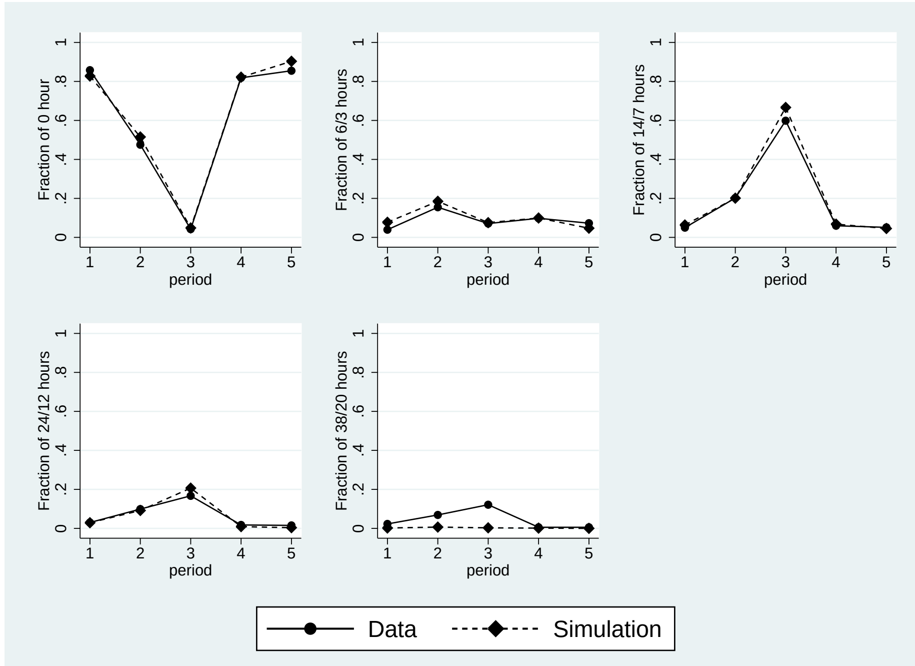


(a) Maternal Work

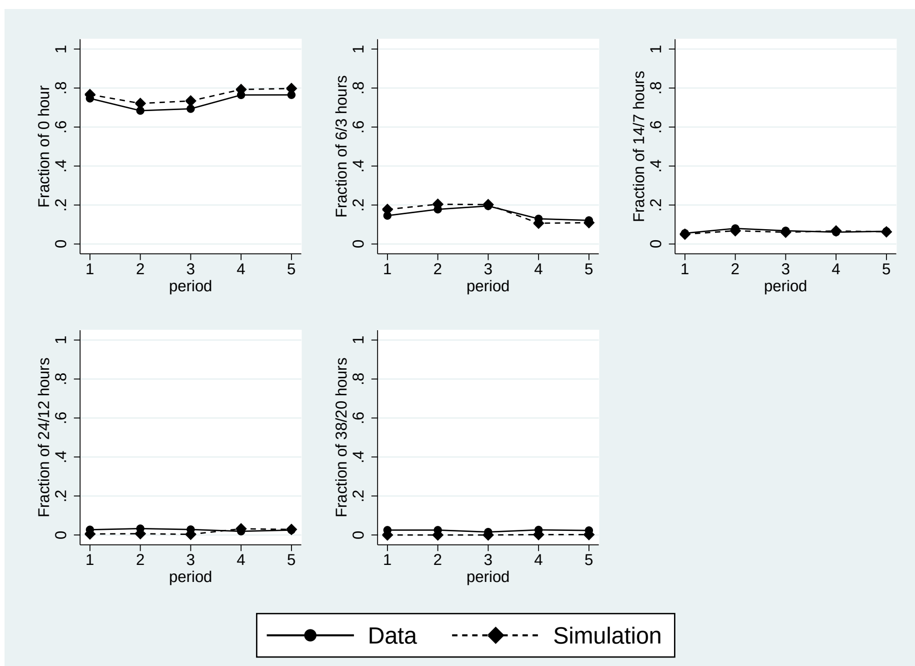


(b) Paternal Child Care

Figure A.5: Model Fit



(a) Formal Child Care



(b) Informal Child Care

Figure A.6: Model Fit

A.8 Additional Counterfactual Results

	Ages	Benchmark	Difference From Benchmark					
			No	Work Requirement		Income Eligibility		
			Restriction	> 0 hours	> 15 hours	< $ 1,500	< $ 2,000	< $ 2,500
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cognitive Skill	6 to 7	0.0000	0.0249	0.0101	0.0011	0.0105	0.0174	0.0219
	8 to 9	0.0000	0.0152	0.0058	0.0000	0.0066	0.0109	0.0136
	10 to 11	0.0000	0.0111	0.0039	-0.0005	0.0050	0.0082	0.0102
Non-Cognitive Skill	6 to 7	0.0000	-0.0352	-0.0235	-0.0152	-0.0031	-0.0189	-0.0257
	8 to 9	0.0000	-0.0190	-0.0130	-0.0087	-0.0031	-0.0101	-0.0137
	10 to 11	0.0000	-0.0113	-0.0080	-0.0055	-0.0031	-0.0058	-0.0080

Note: Benchmark is a scenario without child care subsidy and income transfer. No Restriction is a child care subsidy scenario without a work requirement and income test. Work Requirement is a child care subsidy scenario with a minimum work hours requirement for mothers. Income Eligibility is a child care subsidy scenario with income cutoffs. The values in Column 1 are averages in Benchmark. Cognitive and Non-Cognitive skills are restandardized, using Benchmark's means and standard deviations.

Table A.7: Effects of 100% Child Care Subsidy for Ages 0-5

		Difference/Percentage Change from Benchmark			
	Benchmark	No Restriction	Income Eligibility		
			< $ 1,500	< $ 2,000	< $ 2,500
	(1)	(2)	(3)	(4)	(5)
Government Spending per Week	-	$ 514,006	$ 195,393	$ 297,188	$ 374,219
Cognitive Skill at Ages 10-11	0.0000	0.0111	0.0081	0.0100	0.0109
Non-Cognitive Skill at Ages 10-11	0.0000	-0.0113	-0.0058	-0.0077	-0.0091
Maternal Employment at Preschool Age	53.6%	1.0%	0.5%	0.7%	0.8%
Paternal Child Care at Preschool Age	41.8%	-1.5%	-0.5%	-0.9%	-1.1%
Formal Child Care at Preschool Age	44.2%	41.4%	25.8%	32.8%	37.0%
Informal Child Care at Preschool Age	29.6%	-5.6%	-2.5%	-3.2%	-4.1%
Hours of Maternal work at Preschool Age	18.4	0.4%	-0.4%	-0.3%	0.0%
Hours of Maternal Child Care at Preschool Age	79.2	-5.3%	-2.7%	-3.7%	-4.3%
Hours of Maternal Leisure at Preschool Age	22.7	18.0%	9.4%	12.6%	14.7%
Hours of Paternal Child Care at Preschool Age	6.1	-1.2%	-0.7%	-0.8%	-1.0%
Hours of Formal Child Care at Preschool Age	13.3	18.9%	3.4%	8.2%	11.8%
Hours of Informal Child Care at Preschool Age	8.4	-0.9%	0.1%	-0.4%	-0.7%

Note: Benchmark is a scenario without child care subsidy and income transfer. No Restriction is a child care subsidy scenario without a work requirement and income test. Income Eligibility is a child care subsidy scenario with income tests. The child care subsidy rate decreases by 0.1% for each $1 over the income cutoff. The values in Column 1 are averages in Benchmark. Cognitive and Non-Cognitive skills are restandardized, using benchmark's means and standard deviations. The symbol '$' indicates the Australian dollar. Lifetime utility is the sum of discounted utility at period 1, measures in Australian dollars.

Table A.8: Effects of Child Care Subsidy for Ages 0-5 with Phase-Out Rate

		Difference/Percentage Change from Benchmark					
	Benchmark	No	Work Requirement		Income Eligibility		
		Restriction	> 0 hours	> 15 hours	< \$ 1,500	< \$ 2,000	< \$ 2,500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government Spending per Week	-	\$ 110,387	\$ 110,387	\$ 110,387	\$ 100,859[a]	\$ 110,368	\$ 110,387
Child Care Subsidy Rate	-	30%	33%	39%	100%	67%	49%
Cognitive Skill at Ages 10-11	0.0000	0.0039	0.0016	0.0000	0.0050	0.0061	0.0057
Non-Cognitive Skill at Ages 10-11	0.0000	-0.0037	-0.0029	-0.0023	-0.0031	-0.0039	-0.0040
Maternal Employment at Preschool Age	53.6%	0.1%	0.4%	0.0%	0.2%	0.3%	0.2%
Paternal Child Care at Preschool Age	41.8%	-0.6%	-0.6%	-0.4%	-0.1%	-0.3%	-0.5%
Formal Child Care at Preschool Age	44.2%	17.7%	14.7%	6.5%	14.1%	17.7%	19.3%
Informal Child Care at Preschool Age	29.6%	-1.3%	-1.4%	-0.9%	-1.4%	-1.7%	-1.3%
Hours of Maternal work at Preschool Age	18.4	0.3%	0.2%	0.6%	-0.4%	-0.2%	0.0%
Hours of Maternal Child Care at Preschool Age	79.2	-1.9%	-1.6%	-1.3%	-1.4%	-1.8%	-1.9%
Hours of Maternal Leisure at Preschool Age	22.7	6.4%	5.3%	4.2%	4.9%	6.4%	6.7%
Hours of Paternal Child Care at Preschool Age	6.1	-0.2%	-0.3%	-0.1%	-0.2%	-0.3%	-0.3%
Hours of Formal Child Care at Preschool Age	13.3	4.4%	4.2%	12.4%	-0.8%	0.8%	1.5%
Hours of Informal Child Care at Preschool Age	8.4	-0.1%	-0.3%	-0.5%	0.1%	0.0%	-0.1%
Expenditure on Child at Preschool Age	\$ 188	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%
Consumption at Preschool Age	\$ 1,250	0.5%	0.7%	0.8%	0.5%	0.5%	0.4%
Lifetime Utility	6.593	0.4%	0.4%	0.4%	0.4%	0.4%	0.4%

Note: Benchmark is a scenario without child care subsidy and income transfer. No Restriction is a child care subsidy scenario without a work requirement and income test. Work Requirement is a child care subsidy scenario with a minimum work hours requirement for mothers. Income Eligibility is a child care subsidy scenario with income cutoffs. The values in Column 1 are averages in Benchmark. Cognitive and Non-Cognitive skills are restandardized, using Benchmark's means and standard deviations. The symbol '\$' indicates the Australian dollar. Lifetime utility is the sum of discounted utility at period 1, measured in Australian dollars.

[a] Government spending is smaller than \$110,387 because the child care subsidy rate is over 100% otherwise.

Table A.9: Effects of Child Care Subsidy for Ages 0-5 Holding Government Spending Constant

	Ages	Benchmark	Difference From Benchmark					
			No	Work Requirement		Income Eligibility		
			Restriction	> 0 hours	> 15 hours	< $ 1,500	< $ 2,000	< $ 2,500
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cognitive Skill	6 to 7	0.0000	0.0124	0.0094	0.0058	0.0045	0.0077	0.0099
	8 to 9	0.0000	0.0100	0.0078	0.0045	0.0035	0.0061	0.0079
	10 to 11	0.0000	0.0092	0.0075	0.0041	0.0031	0.0055	0.0072
Non-Cognitive Skill	6 to 7	0.0000	0.0362	0.0239	0.0139	0.0126	0.0216	0.0279
	8 to 9	0.0000	0.0213	0.0143	0.0082	0.0074	0.0128	0.0164
	10 to 11	0.0000	0.0142	0.0096	0.0055	0.0049	0.0085	0.0109

Note: Benchmark is a scenario without child care subsidy and income transfer. No Restriction is a child care subsidy scenario without a work requirement and income test. Work Requirement is a child care subsidy scenario with a minimum work hours requirement for mothers. Income Eligibility is a child care subsidy scenario with income test. The values in Column 1 are averages in Benchmark. Cognitive and Non-Cognitive skills are restandardized, using Benchmark's means and standard deviations.

Table A.10: Effects of 240 AUD Income Transfer for Ages 0-5

	Benchmark	Difference/Percentage Change from Benchmark			
		No	Income Eligibility		
		Restriction	< $ 1,500	< $ 2,000	< $ 2,500
	(1)	(2)	(3)	(4)	(5)
Government Spending per Week	-	$ 1,510,965	$ 822,003	$ 1,099,084	$ 1,274,625
Income Transfer Rate	-	$ 240	$ 240	$ 240	$ 240
Cognitive Skill at Ages 10-11	0.0000	0.0092	0.0050	0.0069	0.0079
Non-Cognitive Skill at Ages 10-11	0.0000	0.0142	0.0076	0.0103	0.0119
Maternal Employment at Preschool Age	53.6%	-1.2%	-2.5%	-1.7%	-1.6%
Paternal Child Care at Preschool Age	41.8%	-0.1%	-0.2%	-0.2%	-0.1%
Formal Child Care at Preschool Age	44.2%	1.3%	-0.2%	0.4%	0.5%
Informal Child Care at Preschool Age	29.6%	-0.1%	-0.3%	-0.4%	-0.2%
Hours of Maternal work at Preschool Age	18.4	-0.1%	0.02%	-0.6%	-0.6%
Hours of Maternal Child Care at Preschool Age	79.2	-0.2%	0.1%	0.003%	-0.03%
Hours of Maternal Leisure at Preschool Age	22.7	1.1%	0.9%	1.0%	1.1%
Hours of Paternal Child Care at Preschool Age	6.1	-0.2%	-0.1%	-0.2%	-0.2%
Hours of Formal Child Care at Preschool Age	13.3	1.1%	-0.6%	-0.7%	-0.2%
Hours of Informal Child Care at Preschool Age	8.4	-0.02%	-0.04%	0.1%	-0.1%
Expenditure on Child at Preschool Age	$ 188	15.8%	8.3%	11.3%	13.1%
Consumption at Preschool Age	$ 1,250	16.4%	8.7%	11.7%	13.7%
Lifetime Utility	6.593	7.7%	4.6%	5.9%	6.7%

Note: Benchmark is a scenario without child care subsidy and income transfer. No Restriction is an income transfer scenario without a work requirement and income test. Income Eligibility is an income transfer scenario with income tests. The income transfer amount decreases by $0.30 for each $1 over the income cutoff. The values in Column 1 are averages in Benchmark. Cognitive and Non-Cognitive skills are restandardized, using benchmark's means and standard deviations. The symbol '$' indicates the Australian dollar. Lifetime utility is the sum of discounted utility at period 1, measured in Australian dollars.

Table A.11: Effects of Income Transfer for Ages 0-5 with Phase-Out Rate

	Benchmark	Difference/Percentage Change from Benchmark					
		No	Work Requirement		Income Eligibility		
		Restriction	> 0 hours	> 15 hours	< $ 1,500	< $ 2,000	< $ 2,500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government Spending per Week	-	$ 1,510,965	$ 1,510,965	$ 1,510,965	$ 1,510,965	$ 1,510,965	$ 1,510,965
Income Transfer Rate	-	$ 240	$ 379	$ 601	$ 609	$ 385	$ 308
Cognitive Skill at Ages 10-11	0.0000	0.0092	0.0122	0.0111	0.0084	0.0088	0.0092
Non-Cognitive Skill at Ages 10-11	0.0000	0.0142	0.0160	0.0155	0.0137	0.0140	0.0141
Maternal Employment at Preschool Age	53.6%	-1.2%	18.0%	0.0%	-7.3%	-4.4%	-2.4%
Paternal Child Care at Preschool Age	41.8%	-0.1%	0.6%	0.2%	-0.5%	-0.2%	-0.2%
Formal Child Care at Preschool Age	44.2%	1.3%	7.7%	8.8%	-2.0%	-0.8%	-0.1%
Informal Child Care at Preschool Age	29.6%	-0.1%	1.7%	0.8%	-0.2%	-0.6%	-0.3%
Hours of Maternal work at Preschool Age	18.4	-0.1%	-9.8%	9.2%	1.1%	-0.1%	-1.1%
Hours of Maternal Child Care at Preschool Age	79.2	-0.2%	-0.5%	-1.0%	0.2%	0.1%	0.05%
Hours of Maternal Leisure at Preschool Age	22.7	1.1%	-0.9%	-0.3%	2.1%	1.6%	1.4%
Hours of Paternal Child Care at Preschool Age	6.1	-0.2%	-0.1%	0.2%	-0.1%	-0.3%	-0.2%
Hours of Formal Child Care at Preschool Age	13.3	1.1%	-2.5%	3.1%	0.6%	-0.5%	-0.2%
Hours of Informal Child Care at Preschool Age	8.4	-0.02%	-0.4%	0.3%	0.0%	0.3%	-0.1%
Expenditure on Child at Preschool Age	$ 188	15.8%	17.1%	17.3%	15.1%	15.3%	15.4%
Consumption at Preschool Age	$ 1,250	16.4%	17.6%	17.5%	15.8%	16.0%	16.1%
Lifetime Utility	6.593	7.7%	6.3%	5.4%	7.9%	8.0%	8.0%

Note: Benchmark is a scenario without child care subsidy and income transfer. No Restriction is an income transfer scenario without a work requirement and income test. Work Requirement is an income transfer scenario with a minimum work hours requirement for mothers. Income Eligibility is an income transfer scenario with income cutoffs. The values in Column 1 are averages in Benchmark. Cognitive and Non-Cognitive skills are restandardized, using Benchmark's means and standard deviations. The symbol '$' indicates the Australian dollar. Lifetime utility is the sum of discounted utility at period 1, measured in Australian dollars.

Table A.12: Effects of Income Transfer for Ages 0-5 Holding Government Spending Constant

	Benchmark (1)	Difference/ Percentage Change from Benchmark: Child Care Subsidy (2)	Income Transfer (3)
Government Spending per Week	-	\$ 514,006	\$ 514,006
Child Care Subsidy Rate or Income Transfer Rate	-	100%	\$ 82
Cognitive Skill at Ages 10-11	0.0000	0.0111	0.0032
Non-Cognitive Skill at Ages 10-11	0.0000	-0.0113	0.0049
Maternal Employment at Preschool Age	53.57%	1.0%	-0.4%
Paternal Child Care at Preschool Age	41.83%	-1.5%	-0.1%
Formal Child Care at Preschool Age	44.23%	41.4%	0.4%
Informal Child Care at Preschool Age	29.61%	-5.6%	-0.1%
Hours of Maternal work at Preschool Age	18.38	0.4%	0.02%
Hours of Maternal Child Care at Preschool Age	79.20	-5.3%	-0.04%
Hours of Maternal Leisure at Preschool Age	22.68	18.0%	0.3%
Hours of Paternal Child Care at Preschool Age	6.09	-1.2%	-0.05%
Hours of Formal Child Care at Preschool Age	13.32	18.9%	0.1%
Hours of Informal Child Care at Preschool Age	8.37	-0.9%	-0.03%
Expenditure on Child at Preschool Age	\$ 187.55	0.2%	5.4%
Consumption at Preschool Age	\$ 1,250	3.9%	5.6%
Lifetime Utility	6.593	1.6%	2.6%

Note: Benchmark is a scenario without child care subsidy and income transfer. Child Care Subsidy and Income Transfer are scenarios with no maternal work requirement and income test. The subsidy rate is 100% in Child Care Subsidy scenario. The values in Column 1 are averages in Benchmark. Cognitive and Non-Cognitive skills are restandardized, using Benchmark's means and standard deviations. The symbol '$' indicates the Australian dollar. Lifetime utility is the sum of discounted utility at period 1, measured in Australian dollars.

Table A.13: Comparison between Child Care Subsidy and Income Transfer

		Difference/Percentage Change from Benchmark					
	Benchmark	No	Work Requirement		Income Eligibility		
		Restriction	> 0 hours	> 15 hours	< $ 1,500	< $ 2,000	< $ 2,500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government Spending per Week	-	$ 514,006	$ 437,108	$ 352,511	$ 100,859	$ 217,132	$ 317,320
Income Transfer Rate	-	$ 82	$ 122	$ 166	$ 47	$ 58	$ 66
Cognitive Skill at Ages 10-11	0.0000	0.0032	0.0036	0.0027	0.0011	0.0018	0.0024
Non-Cognitive Skill at Ages 10-11	0.0000	0.0049	0.0048	0.0037	0.0017	0.0027	0.0035
Maternal Employment at Preschool Age	53.57%	-0.4%	6.0%	0.0%	-1.2%	-0.7%	-0.6%
Paternal Child Care at Preschool Age	41.83%	-0.1%	0.04%	-0.04%	-0.1%	-0.2%	-0.1%
Formal Child Care at Preschool Age	44.23%	0.4%	2.1%	2.1%	-0.2%	0.1%	0.3%
Informal Child Care at Preschool Age	29.61%	-0.1%	0.9%	0.2%	-0.1%	-0.1%	-0.1%
Hours of Maternal work at Preschool Age	18.38	0.02%	-3.6%	2.2%	0.21%	-0.1%	-0.1%
Hours of Maternal Child Care at Preschool Age	79.20	-0.04%	-0.1%	-0.3%	0.04%	0.01%	-0.01%
Hours of Maternal Leisure at Preschool Age	22.68	0.3%	-0.4%	-0.05%	0.3%	0.3%	0.3%
Hours of Paternal Child Care at Preschool Age	6.09	-0.05%	-0.003%	0.1%	-0.01%	0.0%	0.01%
Hours of Formal Child Care at Preschool Age	13.32	0.1%	-0.8%	1.1%	-0.3%	-0.4%	-0.2%
Hours of Informal Child Care at Preschool Age	8.37	-0.03%	-0.2%	0.1%	-0.04%	-0.003%	0.02%
Expenditure on Child at Preschool Age	$ 188	5.4%	5.0%	4.1%	1.9%	3.0%	3.9%
Consumption at Preschool Age	$ 1,250	5.6%	5.1%	4.1%	2.0%	3.2%	4.0%
Lifetime Utility	6.593	2.6%	2.0%	1.4%	1.1%	1.6%	2.0%

Note: Benchmark is a scenario without child care subsidy and income transfer. No Restriction is an income transfer scenario without a work requirement and income test. Work Requirement is an income transfer scenario with a minimum work hours requirement for mothers. Income Eligibility is an income transfer scenario with income cutoffs. The values in Column 1 are averages in Benchmark. Cognitive and Non-Cognitive skills are restandardized, using Benchmark's means and standard deviations. The symbol '$' indicates the Australian dollar. Lifetime utility is the sum of discounted utility at period 1, measured in Australian dollars.

Table A.14: Effects of Income Transfer for Ages 0-5 Corresponding to Table 1.2

Weight		Program	Government Spending per Week		Rate	Maternal Work Requirement	Income Cutoff
Cognitive	Non-Cognitive						
25%	75%	Child Care Subsidy	-	-	-	-	-
		Income Transfer	$ 746,403	100.0%	$ 257	Yes (more than 0 hour)	$ 2,799
57%	43%	Child Care Subsidy	$ 51,739	6.9%	61%	No	$ 1,515
		Income Transfer	$ 694,515	93.1%	$ 258	Yes (more than 0 hour)	$ 2,590
75%	25%	Child Care Subsidy	$ 229,594	30.8%	85%	No	$ 2,336
		Income Transfer	$ 516,754	69.2%	$ 178	Yes (more than 0 hour)	$ 2,948

Note: The symbol '$' indicates the Australian dollar.

Table A.15: Optimal Mix of Child Care Subsidy and Income Transfer

		Weights on Cognitive/Non-Cognitive Skills		
	Benchmark	25%/75%	57%/43%	75%/25%
	(1)	(2)	(3)	(4)
Cognitive Skill at Ages 10-11	0.0000	0.0066	0.0098	0.0131
Non-Cognitive Skill at Ages 10-11	0.0000	0.0082	0.0056	-0.0005
Maternal Employment at Preschool Age	53.6%	11.0%	11.0%	8.5%
Paternal Child Care at Preschool Age	41.8%	0.3%	0.2%	-0.6%
Formal Child Care at Preschool Age	44.2%	4.0%	13.6%	29.7%
Informal Child Care at Preschool Age	29.6%	0.9%	0.1%	-2.0%
Hours of Maternal work at Preschool Age	18.4	-7.1%	-7.4%	-5.1%
Hours of Maternal Child Care at Preschool Age	79.2	-0.2%	-1.1%	-3.1%
Hours of Maternal Leisure at Preschool Age	22.7	-0.6%	2.7%	9.5%
Hours of Paternal Child Care at Preschool Age	6.1	-0.1%	-0.2%	-0.6%
Hours of Formal Child Care at Preschool Age	13.3	-2.5%	-4.1%	3.2%
Hours of Informal Child Care at Preschool Age	8.4	-0.3%	-0.3%	-0.2%
Expenditure on Child at Preschool Age	$ 188	8.4%	7.8%	5.9%
Consumption at Preschool Age	$ 1,250	8.6%	8.2%	7.5%
Lifetime Utility	6.593	3.4%	3.3%	3.2%

Note: Benchmark is a scenario without child care subsidy and income transfer. The values under Benchmark are averages. The values in Columns 2 to 4 are differences or percentage changes from Benchmark. Cognitive and Non-Cognitive skills are restandardized, using Benchmark's means and standard deviations. The symbol '$' indicates the Australian dollar. Lifetime utility is the sum of discounted utility at period 1, measured in Australian dollars.

Table A.16: Effects of Optimal Policy by Different Weights

Appendix B: Appendix for Chapter 2

B.1 Summary Index of Cognitive Ability Test Scores

The following three test scores (two for children of age 5) are used to construct a summary index: Letter-Word Identification (LW), Passage Comprehension (PC) and Applied Problems (AP) (LW and AP for children of age 5). These test scores have a mean of 100 for each age group and a standard deviation of 15. They are renormalized with a mean of zero and a standard deviation of one. After the renormalization, a summary index of the renormalized test scores is constructed in a similar way to Anderson (2008) and Carneiro and Ginja (2014). The summary index is a weighted average of the three renormalized test scores (for children of age 5, two renormalized test scores since the PC was not conducted for them). The weight on each test score for each age is the sum of its corresponding row in the inverse of the variance covariance matrix of the renormalized test scores for each age. This approach ensures that test scores that are less correlated with each other receive more weight, so that we can weight more on new information.

B.2 Measure of Non-Maternal Childcare Time

Several assumptions and imputations are made due to the inconsistency in the data when calculating the cumulative non-maternal childcare time. Primary caregivers were

Age	Summary[a] Index	Letter-Word Identification	Passage Comprehension	Applied Problems	Number of Observations
5 – 13	-0.164	-0.227	-0.124[b]	-0.114	490
	(0.899)	(1.083)	(0.989)	(1.026)	
5	-0.512	-0.531		-0.478	35
	(0.969)	(0.996)		(1.361)	
6	-0.240	-0.162	-0.076	-0.336	49
	(0.956)	(1.190)	(1.161)	(1.076)	
7	0.086	0.042	0.158	0.004	56
	(0.960)	(1.027)	(1.137)	(1.029)	
8	0.153	-0.014	0.206	0.121	42
	(0.941)	(1.171)	(0.978)	(1.168)	
9	-0.011	-0.265	0.058	0.085	44
	(0.805)	(1.005)	(0.840)	(0.893)	
10	0.103	-0.056	0.103	0.189	59
	(0.788)	(0.911)	(0.836)	(0.808)	
11	-0.335	-0.325	-0.404	-0.174	82
	(0.815)	(1.141)	(0.859)	(0.978)	
12	-0.330	-0.303	-0.417	-0.191	79
	(0.713)	(1.010)	(0.738)	(0.863)	
13	-0.323	-0.471	-0.294	-0.305	44
	(1.101)	(1.241)	(1.258)	(1.131)	

Note: Scores are normalized with mean = 0 and standard deviation = 1. Standard deviations are in parentheses.

[a] Summary index is a weighted average of the three standardized test scores (for children of age 5, two standardized test scores), where the weight is the row sum in the inverse of the variance covariance matrix of the standardized test scores.

[b] The number of observations for Passage Comprehension is 455.

Table B.1: Cognitive Ability Test Scores

asked the same questions about non-maternal childcare in both 1997 and 2002 unless the child first started non-maternal childcare after entering kindergarten. However, reports of some primary caregivers in the 2002 wave were inconsistent with the reports in the 1997 wave. Furthermore, primary caregivers could answer the question about the length of non-maternal childcare use in years rather than months, so that they could say that, for example, an arrangement started at 2 years old and ended at 2 years old. To deal with these problems, the following assumptions and imputations are made: 1) the information in the 1997 wave is more accurate than in the 2002 wave because the recall period is shorter; 2) if a new arrangement in the 2002 wave began before the child's age in the 1997 wave, assume that it began at the child's age in the 1997 wave; 3) if a new arrangement in the 2002 wave began and ended before the child's age in the 1997 wave, ignore the arrangement; 4) if only the number of years is reported for the age of the start and/or end of an arrangement, multiply it by 12 to convert in the unit of months; 5) if the start age of an arrangement is the same as the end age of the arrangement, assume that the arrangement was used for 6 months.

B.3 Overidentification Tests and Explanatory Power of Instruments

The fact that we have more instruments than endogenous variables allows us to conduct the Sargan-Hansen test, which is a test of overidentifying restrictions. The joint null hypothesis of the Sargan-Hansen test is that the instruments are correctly excluded from the second stage estimation. The first row of Table B.2 shows the result of the Sargan-Hansen test. The p value for the test is 0.153, so the null hypothesis is not rejected at the 10% significance level. The overidentification test is also conducted for each subset of instruments listed in Table 2.1, given that other instruments are valid. The results of the tests for these subsets of instruments are also reported in Table B.2. All of the p values for these tests are over 0.100, which indicate that, at the 10% significance level, we cannot reject the null hypothesis that the subset of instruments has no direct effect on child cognitive achievement, given that other instruments are valid.

To check the power of the instruments, F-tests for joint significance of the instruments in the first stage estimation are conducted. Table B.3 shows the result of the F test for each endogenous variable. The F statistics for three endogenous variables in the baseline model

	χ^2	p value
Sargan-Hansen test	147.57	0.153
Time Limits	48.47	0.142
Work Requirement	32.57	0.632
AFDC Benefits	10.11	0.607
EITC	8.48	0.205
Family Leave Policy	27.83	0.222
Wages	25.38	0.115

Table B.2: Overidentification Tests

	R^2 Excluding All Instruments	Incremental R^2	F statistic	p value
Cumulative Non-Maternal Childcare	0.263	0.349	12.76	(0.000)
Cumulative Formal Childcare	0.174	0.457	18.56	(0.000)
Cumulative Informal Childcare	0.193	0.319	13.07	(0.000)
Cumulative Mother's Hours of Work	0.373	0.296	15.09	(0.000)
Log Cumulative Family Income	0.431	0.295	26.02	(0.000)

Table B.3: Explanatory Power of Instruments

are 12.76 (cumulative non-maternal childcare time), 15.09 (cumulative mother's hours of work) and 26.02 (cumulative family income). These are large enough according to the rule of thumb, that is, an F statistic greater than 10, so the instruments have sufficient explanatory power. In addition, adding excluded instruments increases R^2 by around 30% for these three endogenous variables. Two types (formal and informal) of non-maternal childcare time also show similar results.

B.4 Nonlinear Effects

I examine the nonlinear effects of non-maternal childcare and maternal work, estimating a specification that includes squares of cumulative non-maternal childcare and cumulative mother's hours of work. Table B.4 shows the result. The coefficient estimates for the linear

Dependent Variable: Summary Index	Main Result (1)	Incl. Squares (2)
Cumulative Non-Maternal Childcare	-0.409***	-0.645***
	(0.116)	(0.249)
Cumulative Non-Maternal Childcare^2		0.243
		(0.199)
Cumulative Mother's Hours of Work	0.269**	-0.154
	(0.124)	(0.340)
Cumulative Mother's Hours of Work^2		0.351
		(0.243)
Log Cumulative Family Income	0.180***	0.158**
	(0.0592)	(0.0640)
Mother's Education at Child Birth	0.0484**	0.0482**
	(0.0216)	(0.0217)

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments. Cumulative non-maternal childcare and mother's hours of work are scaled down by dividing by 10,000, so the estimates of their coefficients are scaled up by 10,000.
* p<0.10 ** p<0.05 *** p<0.01

Table B.4: Nonlinear Effects of Non-Maternal Childcare and Maternal Work of non-maternal childcare and maternal work are negative, and those for the squares of them are positive. However, all estimates except the linear for cumulative non-maternal childcare are imprecisely estimated. The hypothesis that coefficients on two square terms (non-maternal childcare time and hours of maternal work) are jointly zero is also tested. The joint significance test shows that, at the 10% significance level, we cannot reject the hypothesis ($\chi^2 = 4.32$, p value $= 0.115$).

The estimates imply that additional hours of non-maternal childcare have a smaller negative impact on children who spend more hours of non-maternal childcare. Specifically, consider the effect of a 2000 hour increase in non-maternal childcare (or additional year of full-time non-maternal childcare) at three different hours of non-maternal childcare: (1) 0 hour, (2) 2,000 hours, and (3) 4,000 hours. The estimated effect of the 2,000 increase in non-maternal childcare is a reduction of 0.129 standard deviations in cognitive achievement at 0 hour of non-maternal childcare, and the estimated effect is a decrease of 0.110 and 0.090 standard deviations at 2,000 and 4,000 hours, respectively. The marginal effect of non-maternal childcare is zero when cumulative hours of non-maternal childcare is 13,272 hours, which is larger than full-time use of non-maternal childcare for 5 years (i.e., 10,000 hours). This suggests that the marginal effect of non-maternal childcare is negative in a range of possible hours of non-maternal childcare (i.e., 0 to 10,000 hours).

Similar to the effect of non-maternal childcare, the marginal effect of maternal work is more negative (or less positive) for mothers who work for less hours, but it is less negative (or more positive) for mothers who work for more hours. For example, consider the effect of a 2000 hour increase in maternal work (or additional year of full-time maternal work) at three different hours of non-maternal childcare: (1) 0 hour, (2) 2,000 hours, and (3) 4,000 hours. The estimated effect of the 2,000 hour increase in maternal work is a reduction of

0.031 and 0.003 standard deviations at 0 and 2,000 hours of maternal work, respectively, and it is an increase of 0.025 standard deviations at 4,000 hours of maternal work. The marginal effect of maternal work is zero at 2,194 hours of cumulative mother's hours of work, which is close to a year full-time work (i.e., 2,000 hours).

B.5 Additional Robustness and Sensitivity Check

Since IV estimates can depend on which set of instruments to be used, sensitivity to various sets of the instruments is examined.[166] This analysis is also useful because some sets of instruments show quite small p values for overidentification test. In Table B.5, the GMM results for 7 subsets of the original instruments are reported from column 2 to 8. In column 2, only the instruments used in Bernal and Keane (2011) are included. The GMM estimate of the effect of non-maternal childcare is slightly more negative than the estimate with the original instruments. In column 3, the instruments used in Bernal and Keane (2011) are excluded. The estimated effect of non-maternal childcare is slightly less negative, and it is imprecisely estimated. Column 4 shows the result for using instruments related to policy changes during 1990's, and there is little impact on the estimated effect of non-maternal childcare. In column 5, all instruments except EITC in column 4 are used. Note that EITC provides exogenous variation only over time, but instruments used in column 5 provide exogenous variation mainly across states. The estimated negative effect of non-maternal childcare is larger than the result using original instruments, but the difference is not large. In column 6, individual-specific instruments are excluded and only state-specific instruments are included. This reduces the magnitude of the estimate to -0.202, which is statistically insignificant. In column 7, instruments that show low p values for overidentifying test are

[166]The result for formal and informal childcare is shown in Table B.18. The results of F-tests and overidentification tests are reported in Table B.19.

Dependent Variable: Summary Index	Original Instruments (1)	TL, WR, AFDC (2)	EITC, FL, Wages (3)	TL, WR, EITC, FL (4)	TL, WR, FL (5)	Only State-Specific IVs (6)	TL, EITC, FL, Wages (7)	WR, AFDC (8)
Cumulative Non-Maternal Childcare[a]	-0.409***	-0.463***	-0.349	-0.367***	-0.495***	-0.202	-0.389**	-0.287
	(0.116)	(0.176)	(0.265)	(0.135)	(0.143)	(0.141)	(0.167)	(0.270)
Cumulative Mother's Hours of Work[a]	0.269**	0.203	0.348	0.241*	0.301**	0.141	0.450**	0.160
	(0.124)	(0.156)	(0.286)	(0.144)	(0.148)	(0.136)	(0.197)	(0.223)
Log Cumulative Family Income	0.180***	0.284***	0.386**	0.230***	0.226***	0.239***	0.298***	0.498***
	(0.0592)	(0.0822)	(0.157)	(0.0674)	(0.0704)	(0.0728)	(0.105)	(0.141)
Number of Instruments	134	88	47	104	98	108	86	48

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is GMM. TL = Time limits; WR = Work requirements; AFDC = Aid to Families with Dependent Children benefits; EITC = Earned income tax credit; FL = Family leave policy.

[a] These variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.

* $p<0.10$ ** $p<0.05$ *** $p<0.01$

Table B.5: Sensitivity to the Instruments

Dependent Variable: Summary Index	Main Result (1)	Excl. Family Income (2)	Excl. Maternal Employment (3)	Excl. Both (4)
Cumulative Non-Maternal Childcare[a]	-0.409***	-0.428***	-0.286***	-0.176*
	(0.116)	(0.123)	(0.105)	(0.107)
Cumulative Mother's Hours of Work[a]	0.269**	0.473***		
	(0.124)	(0.119)		
Log Cumulative Family Income	0.180***		0.233***	
	(0.0592)		(0.0549)	

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments.
[a] These variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.
* p<0.10 ** p<0.05 *** p<0.01

Table B.6: Sensitivity to Omitting Maternal Employment and/or Family Income

used, and the estimated effect of non-maternal childcare has little impact from this. Column 8 shows the result without using instruments in column 7. The estimate is -0.287, and it is statistically insignificant. Overall, the negative effect of non-maternal childcare is quite robust to various sets of the instruments, and the estimates are fairly close to the estimate using the original instruments.

B.6 Individual Cognitive Achievement Tests and Non-Cognitive Outcomes

Many previous studies find that inputs for child cognitive production function have different effects on different test scores. To examine this, the main regression model is estimated using each test score as dependent variable. In column 1 and 2 of Table B.10, the results for LW are shown. The estimated effect of non-maternal childcare is -0.226. Similar to the results earlier, informal childcare has a larger negative effect than formal childcare. The results for PC are close to that for LW. Column 3 shows that the estimated effects of non-maternal childcare is -0.254. The close results of LW and PC would be because

Dependent Variable: Summary Index	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative Non-Maternal Childcare[a]	-0.409***	-0.449***	-0.436***	-0.371***	-0.459***	-0.396***
	(0.116)	(0.117)	(0.116)	(0.125)	(0.114)	(0.125)
Cumulative Mother's Hours of Work[a]	0.269**	0.312**	0.305**	0.162	0.334***	0.217
	(0.124)	(0.122)	(0.123)	(0.134)	(0.122)	(0.132)
Log Cumulative Family Income	0.180***	0.191***	0.166***	0.147**	0.191***	0.162***
	(0.0592)	(0.0597)	(0.0593)	(0.0642)	(0.0620)	(0.0591)
Mother's Education at Child Birth	0.0484**	0.0500**	0.0494**	0.0601***	0.0485**	0.0559***
	(0.0216)	(0.0213)	(0.0215)	(0.0212)	(0.0216)	(0.0209)
Existence of Siblings Aged 5 or Less	Y	N	Y	Y	N	N
Existence of Siblings Aged 6 to 17	Y	Y	Y	Y	Y	Y
Existence of Siblings Aged 1 or Less	N	Y	N	N	Y	Y
Existence of Siblings Aged 2 to 5	N	Y	N	N	Y	Y
Avg. # of Children Aged 5 or Less[b]	N	N	Y	N	Y	N
Avg. # of Children under 18[b]	N	N	N	Y	N	Y

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments. Column 1 shows the main result in Table 2.6.

[a] These variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.

[b] Average for the period when a child is age 0 to 5.

* p<0.10 ** p<0.05 *** p<0.01

Table B.7: Sensitivity to Changes in Control Variables for Siblings

both are tests for reading skills. In column 5 and 6, the results for AP, which is a test for math skills, are reported. In column 5, the estimate shows a larger negative effect than the estimates for LW and PC. This implies that non-maternal childcare has a more adverse effect on children's math skills than reading skills. Column 6 shows that formal childcare has a slightly large negative effect than informal childcare, implying that children's math skills are negatively affected by non-maternal childcare regardless of type of non-maternal childcare.

Many studies show that non-cognitive skills are also important determinants of labor market outcomes, so it is interesting to examine the effect of non-maternal childcare on non-cognitive outcomes. For this analysis, Behavior Problems Index (BPI) and Positive Behaviors Scale (PBS) are used as measures of non-cognitive skills. The BPI uses 27

Dependent Variable: Summary Index	(1)	(2)	(3)	(4)
Cumulative Non-Maternal Childcare[a]	-0.394***	-0.366***	-0.299***	-0.294***
	(0.121)	(0.125)	(0.108)	(0.112)
Cumulative Mother's Hours of Work[a]	0.280**	0.270**	0.337***	0.340***
	(0.121)	(0.124)	(0.0978)	(0.105)
Log Cumulative Family Income	0.183***	0.200*	0.131***	0.119
	(0.0550)	(0.110)	(0.0475)	(0.108)
Mother's Education at Child Birth	0.0516**	0.0591***	0.0447**	0.0420**
	(0.0204)	(0.0201)	(0.0178)	(0.0170)
Log Average Yearly Family Income After Child Age 5	N	Y	N	Y
Ever Attended Private School/Special Class	N	N	Y	Y

Note: The number of observations is 467. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments.
[a] These variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.
* p<0.10 ** p<0.05 *** p<0.01

Table B.8: Sensitivity to including inputs during schooling

Dependent Variable: Summary Index	(1)	(2)	(3)	(4)
Cumulative Non-Maternal Childcare[a]	-0.409***	-0.489***	-0.355***	-0.431***
	(0.116)	(0.142)	(0.127)	(0.145)
Cumulative Mother's Hours of Work[a]	0.269**	0.355**	0.244**	0.430***
	(0.124)	(0.156)	(0.123)	(0.161)
Log Cumulative Family Income	0.180***	0.219***	0.199***	0.227***
	(0.0592)	(0.0684)	(0.0600)	(0.0656)
Mother's Education at Child Birth	0.0484**	0.0479**	0.0417*	0.0410*
	(0.0216)	(0.0225)	(0.0215)	(0.0216)
Work More Hours than Hours of Non-Maternal Childcare	N	Y	N	Y
Work and No use of Non-Maternal Childcare	N	N	Y	Y

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments. Column 1 shows the main result in Table 2.6
[a] These variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.
* p<0.10 ** p<0.05 *** p<0.01

Table B.9: Controlling for Mothers Working More Hours than Hours of Non-Maternal Childcare

Dependent Variable	Letter-Word Identification		Passage Comprehension		Applied Problems	
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative Non-Maternal Childcare[a]	-0.226*		-0.254*		-0.588***	
	(0.130)		(0.130)		(0.149)	
Cumulative Formal Childcare[a]		-0.0675		-0.151		-0.605***
		(0.218)		(0.186)		(0.217)
Cumulative Informal Childcare[a]		-0.320**		-0.299**		-0.582***
		(0.150)		(0.148)		(0.160)
Cumulative Mother's Hours of Work[a]	0.167	0.190	0.449***	0.465***	0.430***	0.430***
	(0.160)	(0.160)	(0.135)	(0.137)	(0.137)	(0.138)
Log Cumulative Family Income	0.203**	0.203**	0.0905	0.0817	0.333***	0.338***
	(0.0846)	(0.0857)	(0.0737)	(0.0750)	(0.0622)	(0.0623)
N	490		455[b]		490	

Note: Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments.
[a] Cumulative variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.
[b] PC scores are available for children aged from 6, so children aged 5 are dropped.
* p<0.10 ** p<0.05 *** p<0.01

Table B.10: Result for Each Cognitive Achievement Test

Dependent Variable	Behavior Problems Index		Positive Behaviors Scale	
	(1)	(2)	(3)	(4)
Cumulative Non-Maternal Childcare[a]	0.494***		-0.418***	
	(0.146)		(0.158)	
Cumulative Formal Childcare[a]		0.649***		-0.378**
		(0.203)		(0.172)
Cumulative Informal Childcare[a]		0.441***		-0.434**
		(0.162)		(0.200)
Cumulative Mother's Hours of Work[a]	-0.643***	-0.649***	0.386**	0.378**
	(0.176)	(0.176)	(0.178)	(0.179)
Log Cumulative Family Income	-0.0774	-0.0886	-0.0656	-0.0578
	(0.0824)	(0.0836)	(0.0842)	(0.0839)

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments.
[a] Cumulative variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.
* p<0.10 ** p<0.05 *** p<0.01

Table B.11: Effect of Non-Maternal Childcare on Non-Cognitive Outcomes questions[167] to measure the severity of behavior problems. The higher value of the BPI indicates that the child has more behavior problems. The PBS uses 10 questions[168] to measure emotional or social skill. The higher value of the PBS implies a higher level of positive behaviors. These two measures are normalized with a mean of zero and a standard deviation of one. Table B.11 reports the results for non-cognitive outcomes. The estimates imply that full-time use of non-maternal childcare for 5 years increases behavior problems by 0.494 standard deviations, and it decreases positive behaviors by 0.418 standard deviations. Considering type of non-maternal childcare, both formal and informal childcare have adverse effects on behavior problems and positive behaviors. The results here provide evidence against the possibility that positive effects on non-cognitive outcomes could offset negative effects on cognitive outcomes.

B.7 Tables for Additional Results

[167] For example, how often he/she has sudden changes in mood or feeling, how often he/she is too fearful or anxious, how often he/she bullies, or is cruel or mean to others. and how often he/she is stubborn, sullen, or irritable.

[168] For example, how much he/she is curious and exploring, likes new experiences, how much he/she thinks before acting, is not impulsive, and how much he/she can get over being upset quickly.

Dependent Variable: Summary Index	OLS (1)	TSLS (2)	GMM (3)	TSLS 31 factors[a] (4)	GMM 31 factors[a] (5)	TSLS 11 factors[b] (6)	GMM 11 factors[b] (7)	TSLS 14 factors[c] (8)	GMM 14 factors[c] (9)
Cumulative Non-Maternal Childcare[d]	-0.196	-0.492**	-0.409***	-0.165	-0.332	-0.255	-0.449	-0.487	-0.415
	(0.150)	(0.196)	(0.116)	(0.393)	(0.349)	(0.709)	(0.698)	(0.503)	(0.490)
Cumulative Mother's Hours of Work[d]	-0.00262	0.346	0.269**	0.282	0.428	1.049	1.080	1.042*	1.061*
	(0.170)	(0.223)	(0.124)	(0.401)	(0.370)	(0.709)	(0.695)	(0.588)	(0.570)
Log Cumulative Family Income	0.185**	0.220*	0.180***	0.299	0.312*	0.0802	0.161	-0.188	-0.232
	(0.0932)	(0.122)	(0.0592)	(0.195)	(0.172)	(0.297)	(0.282)	(0.309)	(0.298)
Child's Age at Assessment	-0.0330**	-0.0325**	-0.0382***	-0.0315**	-0.0425***	-0.0293**	-0.0370***	-0.0306**	-0.0283**
	(0.0139)	(0.0131)	(0.00891)	(0.0132)	(0.0118)	(0.0135)	(0.0128)	(0.0133)	(0.0128)
Boy	-0.235**	-0.247***	-0.291***	-0.237**	-0.302***	-0.269**	-0.268***	-0.284***	-0.251**
	(0.0950)	(0.0919)	(0.0525)	(0.0935)	(0.0824)	(0.105)	(0.103)	(0.101)	(0.0989)
Non-White	-0.548***	-0.500***	-0.533***	-0.471***	-0.337**	-0.452**	-0.299	-0.554***	-0.543***
	(0.164)	(0.160)	(0.0815)	(0.171)	(0.154)	(0.194)	(0.187)	(0.185)	(0.177)
Birth Weight	-0.00317	-0.00396*	-0.00475***	-0.00459**	-0.00498***	-0.00537**	-0.00531**	-0.00362	-0.00284
	(0.00207)	(0.00204)	(0.00130)	(0.00205)	(0.00193)	(0.00247)	(0.00243)	(0.00240)	(0.00232)
Birth Order	-0.0532	-0.0346	-0.0231	-0.0325	-0.00599	0.00131	-0.00162	-0.0115	0.000741
	(0.0571)	(0.0546)	(0.0352)	(0.0598)	(0.0545)	(0.0658)	(0.0654)	(0.0592)	(0.0567)
Bad health at Birth	-0.378**	-0.442**	-0.351***	-0.443**	-0.418**	-0.436**	-0.490**	-0.352*	-0.317
	(0.179)	(0.172)	(0.115)	(0.178)	(0.168)	(0.214)	(0.211)	(0.198)	(0.194)
Mother's Age at Child Birth	0.00366	0.00165	0.00276	0.000951	-0.00252	-0.00205	-0.00605	0.000407	-0.00297
	(0.00992)	(0.00974)	(0.00596)	(0.00984)	(0.00934)	(0.0116)	(0.0114)	(0.0116)	(0.0112)
Mother's Education at Child Birth	0.0601**	0.0460	0.0484**	0.0199	0.00556	-0.0120	-0.0170	0.0373	0.0377
	(0.0289)	(0.0303)	(0.0216)	(0.0368)	(0.0339)	(0.0482)	(0.0473)	(0.0440)	(0.0430)
Existence of Sibling under Age 5	-0.133	-0.0958	-0.192**	-0.0508	-0.100	0.0199	0.0106	-0.0746	-0.0256
	(0.137)	(0.133)	(0.0792)	(0.137)	(0.123)	(0.153)	(0.151)	(0.147)	(0.143)
Existence of Sibling Aged 6 to 17	-0.00382	-0.0163	-0.00115	0.0241	0.0706	-0.0825	0.0269	-0.180	-0.194
	(0.162)	(0.158)	(0.0900)	(0.179)	(0.151)	(0.206)	(0.199)	(0.206)	(0.196)

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The original number of instruments is 134.

[a] Factors whose coefficients are statistically significant at the 1% level in the regression of at least one of endogenous variables.

[b] Factors whose coefficients are statistically significant at the 1% level in the regression of at least two of endogenous variables.

[c] Factors whose coefficients are statistically significant at the 5% level in all regressions of endogenous variables.

[d] These variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.

* $p<0.10$ ** $p<0.05$ *** $p<0.01$

Table B.12: Full Estimation Result

Dependent Variable: Children's Education (Years of Schooling) in 2015	
Summary Index	0.492***
	(0.0654)
Child's Age in 2015	0.135***
	(0.0158)
Mother's Education in 2015	0.104***
	(0.0267)
Mother's Age	0.0290***
	(0.0109)
Boy	-0.462***
	(0.109)
Non-White	0.198
	(0.175)
Birth Order	-0.236***
	(0.0635)
Number of Siblings	0.112**
	(0.0564)
Constant	7.717***
	(0.577)
N	854

Note: Ordinary least squares is used for estimation. Standard errors are in parentheses. Sample consists of children whose mother was single for years or more when her child was 0 to 5 years old.
* $p<0.10$ ** $p<0.05$ *** $p<0.01$

Table B.13: Relation between Summary Index and Children's Education in 2015

Dependent Variable: Summary Index	Main Result (1)	Including Mother's Test Score (2)
Cumulative Non-Maternal Childcare[a]	-0.409***	-0.512***
	(0.116)	(0.115)
Cumulative Mother's Hours of Work[a]	0.269**	0.411***
	(0.124)	(0.127)
Log Cumulative Family Income	0.180***	0.0618
	(0.0592)	(0.0693)
Mother's Education at Child Birth	0.0484**	0.0240
	(0.0216)	(0.0225)

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. A dummy for observations that have missing value for mother's test score is also included. The estimation method is two-step GMM with 134 instruments.

[a] These variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.

* $p<0.10$ ** $p<0.05$ *** $p<0.01$

Table B.14: Impact of Including Mother's Test Score on the Estimated Effect of Mother's Hours of Work

Dependent Variable: Summary Index	(1)	(2)
Cumulative Non-Maternal Childcare[a]		
Age 0 to 36 months	-0.796***	
	(0.234)	
Age 36 to 60 months	-0.0513	
	(0.208)	
Cumulative Formal Childcare[a]		
Age 0 to 36 months		0.200
		(0.391)
Age 36 to 60 months		-0.345
		(0.305)
Cumulative Informal Childcare[a]		
Age 0 to 36 months		-0.932***
		(0.238)
Age 36 to 60 months		0.158
		(0.230)
Cumulative Mother's Hours of Work		
Age 0 to 2 years	0.478*	0.370
	(0.257)	(0.264)
Age 3 to 5 years	0.0668	0.125
	(0.225)	(0.230)
Log Cumulative Family Income		
Age 0 to 2 years	0.0826	0.0516
	(0.0567)	(0.0567)
Age 3 to 5 years	0.197***	0.242***
	(0.0625)	(0.0631)

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments.
[a] These variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.
* $p<0.10$ ** $p<0.05$ *** $p<0.01$

Table B.15: Timing of Non-Maternal Childcare

Formal Childcare		Maternal Employment		Income			
Time (Hours)	Marginal Effect	Time (Hours)	Marginal Effect	Percentiles	Wage[a]	Marginal Effect[b]	Net Effect[c]
2,000	-0.046	0	0		0	0	-0.046
		1,000	0.029	25%	3,618	0.034	0.016
				50%	5,495	0.051	0.034
				75%	7,613	0.071	0.054
		2,000	0.058	25%	13,437	0.125	0.137
				50%	17,559	0.164	0.175
				75%	24,807	0.231	0.243
Informal Childcare		**Maternal Employment**		**Income**			
Time (Hours)	Marginal Effect	Time (Hours)	Marginal Effect	Percentiles	Wage[a]	Marginal Effect[b]	Net Effect[c]
2,000	-0.098	0	0		0	0	-0.098
		1,000	0.029	25%	3,618	0.034	-0.035
				50%	5,495	0.051	-0.018
				75%	7,613	0.071	0.002
		2,000	0.058	25%	13,437	0.125	0.086
				50%	17,559	0.164	0.124
				75%	24,807	0.231	0.192

Note: The GMM estimates using the original instruments in Table 2.6 are used.

[a] Wages for 1,000 and 2,000 hours of work are obtained from the wage distribution of mothers who work for 900 to 1,100 hours and for 1,900 to 2,100 hours, respectively.

[b] The marginal effect of income is calculated by $\beta_3 \times \frac{1}{G} \times \Delta Wage$, where average annual family income is used for G.

[c] Net effect is the sum of column 2, 4 and 7.

Table B.16: Net Effect of Non-Maternal Childcare
under Alternative Assumptions
about Maternal Employment and Wages

Dependent Variable: Summary Index	Main Result (1)	Excl. Family Income (2)	Excl. Maternal Employment (3)	Excl. Both (4)
Cumulative Formal Childcare[a]	-0.232	-0.286	-0.0935	-0.0649
	(0.173)	(0.179)	(0.173)	(0.173)
Cumulative Informal Childcare[a]	-0.489***	-0.492***	-0.357***	-0.217*
	(0.130)	(0.134)	(0.117)	(0.118)
Cumulative Mother's Hours of Work[a]	0.290**	0.489***		
	(0.125)	(0.119)		
Log Cumulative Family Income	0.174***		0.231***	
	(0.0590)		(0.0547)	

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is two-step GMM with 134 instruments.

[a] These variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.

* p<0.10 ** p<0.05 *** p<0.01

Table B.17: Sensitivity to Omitting Family Income and/or Maternal Employment for Formal and Informal Childcare

Dependent Variable: Summary Index	Original Instruments (1)	TL, WR, AFDC (2)	EITC, FL, Wages (3)	TL, WR, EITC, FL (4)	TL, WR, FL (5)	Only State-Specific IVs (6)	TL, EITC, FL, Wages (7)	WR, AFDC (8)
Cumulative Formal Childcare[a]	-0.232	-0.219	0.0175	0.0534	-0.276	0.0528	-0.0484	-0.639
	(0.173)	(0.286)	(0.344)	(0.223)	(0.234)	(0.187)	(0.234)	(0.412)
Cumulative Informal Childcare[a]	-0.489***	-0.427**	-0.653**	-0.507***	-0.569***	-0.347**	-0.600***	-0.169
	(0.130)	(0.186)	(0.326)	(0.147)	(0.155)	(0.163)	(0.210)	(0.283)
Cumulative Mother's Hours of Work[a]	0.290**	0.222	0.351	0.280*	0.317**	0.225	0.522***	0.0792
	(0.125)	(0.166)	(0.273)	(0.144)	(0.149)	(0.142)	(0.195)	(0.234)
Log Cumulative Family Income	0.174***	0.242***	0.441***	0.202***	0.206***	0.209***	0.288***	0.514***
	(0.0590)	(0.0880)	(0.158)	(0.0688)	(0.0721)	(0.0753)	(0.106)	(0.139)
Number of Instruments	134	88	47	104	98	108	86	48

Note: The number of observations is 490. Clustered robust standard errors are in parentheses. Child and family characteristics variables described in Section 2.3 are used for control variables. Dummies for the year and state of birth are included. The estimation method is GMM. TL = Time limits; WR = Work requirements; AFDC = Aid to Families with Dependent Children benefits; EITC = Earned income tax credit; FL = Family leave policy.

[a] These variables are scaled down by dividing by 10,000, so the estimates are scaled up by 10,000.

* $p<0.10$ ** $p<0.05$ *** $p<0.01$

Table B.18: Sensitivity to the Instruments for Formal and Informal Childcare

	All Instruments (1)	TL, WR, AFDC (2)	EITC, FL, Wages (3)	TL, WR, EITC, FL (4)	TL, WR, FL (5)	Only State-Specific IVs (6)	TL, EITC, FL, Wages (7)	WR, AFDC (8)
Panel A: Incremental R^2								
Cumulative Non-Maternal Childcare	0.349	0.230	0.100	0.269	0.253	0.269	0.205	0.120
Cumulative Formal Childcare	0.457	0.269	0.167	0.374	0.335	0.341	0.278	0.138
Cumulative Informal Childcare	0.319	0.228	0.098	0.239	0.235	0.263	0.187	0.124
Cumulative Mother's Hours of Work	0.296	0.223	0.101	0.238	0.221	0.248	0.172	0.117
Log Cumulative Family Income	0.295	0.208	0.098	0.247	0.235	0.243	0.207	0.110
Panel B: F statistic (p value in parentheses)								
Cumulative Non-Maternal Childcare	12.76	5.33	3.61	11.85	13.30	6.10	6.38	1.98
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)
Cumulative Formal Childcare	18.56	4.91	2.19	30.59	68.61	7.65	6.12	2.34
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cumulative Informal Childcare	13.07	3.61	1.84	13.25	13.30	3.41	2.64	2.44
	(0.0000)	(0.0019)	(0.0011)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cumulative Mother's Hours of Work	15.09	5.56	3.48	12.81	13.34	9.98	4.93	2.62
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log Cumulative Family Income	26.02	8.00	5.44	23.70	23.81	11.70	7.34	2.49
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Panel C: Sargan-Hansen test								
χ^2	147.57	96.46	53.07	115.52	110.75	115.46	100.40	43.37
p value	0.153	0.166	0.164	0.153	0.129	0.228	0.094	0.541
Number of Instruments	134	88	47	104	98	108	86	48

Note: TL = Time limits; WR = Work requirements; AFDC = Aid to Families with Dependent Children benefits; EITC = Earned income tax credit; FL = Family leave policy.

Table B.19: First Stage Results of Subsets of the Original Instruments

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