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Mothers working during preschool years and child skills. Does income compensate?*

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Abstract

Increasing mothers' labour supply in a child's preschool years can cause a reduction in time investments that lead to a negative direct effect on mid-childhood and teenage outcomes. But as mothers' work hours increase, income will rise. We ask whether income can compensate for the negative effect of hours by adopting a novel mediation analysis that exploits exogenous variation in both mothers' hours and family income in pre-school years. As expected we find a negative direct effect of an increase in mother's work hours on child test scores at age 11 and 15. However, income fully compensates for this negative direct effect. This is true for the full sample of children, for boys and girls and for children in households whose mother has a low and high level of education.

Keywords: Child development, test scores, parental investments
JEL codes: I22, I24

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1 Introduction

Parental resources of time and money have an important role in explaining the transmission of disadvantage across generations. Children born in more disadvantaged families grow up with lower income resources, poorer parental time investments and worse educational achievements than children born in more privileged families (see McLanahan 2004; Guryan, Hurst, and Kearney 2008; Kalil, Ryan, and Corey 2012, Dotti Sani and Treas 2016). An important target of policies aiming to raise parental time investments and household income is the mother's labour supply. For example maternity leave policies allow working mothers to invest more time with newborn children, while in-work benefits offer financial incentives for mothers to work, to reduce poverty in working families with children. We ask in this paper whether increasing mothers' labour supply in a child's preschool years has a positive or negative effect on child outcomes in childhood and teen years.

There are several challenging issues in answering this question. First, there are two channels though which increased maternal labour supply affects children. On the one hand, an increase in mother' work hours reduces the time available to spend with her child which may harm her child's human capital development. On the other hand, an increase in working hours will raise household income and therefore the resources available to invest in children. To understand how an increase in mothers' work hours affect their children, it is therefore necessary to consider not only the direct effect of mothers' hours worked on child outcomes through a potential reduction in time investments in children, but also the indirect effect through an increase in income. Secondly, we have to deal with the endogeneity of both work hours and income.

While many papers have estimated the effect of mothers' labour supply decisions on children's outcomes; there is a void in our knowledge of the mechanisms through which mothers' work hours affect children's outcomes.[1] We address this research question by (i) estimating the causal total effect of an increase in mothers' hours worked during pre-school

[1] Blau and Grossbergm (1992) and Ermisch and Francesconi (2013) estimate a negative effect of mothers' working hours on child outcomes; whilst Baker and Milligan (2008) estimate a negligible effect. A set of papers analysing the effect of extension to maternity leave on child outcomes have found positive effects for expansions from no paid leave to 12 weeks (Carneiro, Løken, and Salvanes 2015) or effects just for high educated mothers (Liu and Skans 2010, Danzer and Lavy 2013) but otherwise small or no effects on children (Rasmussen 2010, Dustmann and Schönberg 2012, Baker and Milligan 2015, Huebener, Kuehnle, and Spiess 2019).

years on children school achievements; (ii) exploring the mechanisms behind the effect of mother's hours worked by running a mediation analysis that allows us to decompose the causal total effect into the part explained by a time investment reduction (the direct effect) and the one explained by an increase in income (the mediator effect).[2]

We leverage Norwegian population wide administrative data in the analysis, where we focus on first-born children and assess the effect of mothers' work decisions in the years before the child starts school on the child's educational achievements measured by school test scores at age 11 and 15. Household income and mother's work hours in the pre-school period are measured by averaging them over the 5 years from when the child is 1 to 5 years old.[3]

Our first contribution is empirical, aiming to better understand the causal mechanisms explaining the total effect of an increase in mothers' work hours in preschool years on first-born children's educational achievements.[4] Our second main contribution is to adapt the mediation analysis approach (see e.g. Heckman and Pinto 2015) to decompose the total effect of an increase in work hours into the *causal* direct effect and the *causal* mediator effect through income and to extend this approach to address the endogeneity of *both* household income and work hours decisions.

Using the terminology from the mediation analysis literature, our treatment is mothers' working hours and our mediator is household income. Figure 1 depicts the endogeneity issues

[2] We consider household income rather than mothers' income as a mediator. The reason is that we know that labour supply of mothers can substitute for labour supply of fathers and vice versa and we want to capture the total effect of the change in household income associated with changes in mothers' hours.

[3] We exclude the first year after child's birth, owing to the fact that the first year of life is a critical period when the effect of time investments is large and not comparable to the effect for children aged between 1 and 5 (see e.g. Carneiro, Løken, and Salvanes 2015), and parental labour decisions in this period are mainly driven by parental leave entitlement. In our data period in Norway, mothers are entitled to up to 52 weeks of paid leave and fathers are entitled to share a proportion of the leave.

[4] Another paper looking at the effect of hours and income on child's outcome that we became aware of after starting this project is Agostinelli and Sorrenti (2018), who use the US National Longitudinal Study of Youth 1979. Agostinelli and Sorrenti (2018) consider shocks to the local (state level) female labour demand and changes in the Earned Income Tax Credit benefits as instruments for mothers' work hours and household income. Our paper differs as we focus on parental inputs in the pre-school years which are an important stage of child development and on medium- and long-run effects. In contrast to our analysis, Agostinelli and Sorrenti (2018) consider a long period from 1988 to 2000, focus on contemporaneous effects of household income and mothers' work hours on child's outcomes and impose that these effects do not differ across child's age for the period from 6 to 18. We know from evidence including Cunha and Heckman (2007) that the child production function varies across stages of childhood. In a final difference, we causally identify the effect of the mother's hours on income in order to implement a causal decomposition analysis.

of treatment and mediator inherent in our mediation (decomposition) analysis. In both panels A and B, we use arrows to represent each of the causal pathways from the treatment - the mothers' labour hours H - to the child outcomes Y. The direct effect from H to Y is captured by the curved arrow from H to Y; and the mediator effect from H to Y through I is captured by the two horizonal arrows from H to I and from I to Y. Panel A considers the endogeneity of the treatment, whereby unobservable traits that determine mothers' labour hours (u^H) can be also relevant in explaining household income and the child outcome. In empirical applications where, contrary to our case, the treatment has been randomized (e.g. Imai, Keele, Tingley, and Yamamoto 2011, Heckman, Pinto, and Savelyev 2013, Heckman and Pinto 2015, Acharya, Blackwell, and Sen 2016 and Aklin and Bayer 2017), there are no unobserved variables u^H that explain the treatment and the endogeneity issue in Panel A does not exist.

In addition, all mediation analyses are exposed to the endogeneity of the mediator (see Panel B), whereby unobservable traits which determine the mediator (u^I) are potential determinants of the outcome Y. Studies based on randomized treatments solve the issue of endogeneity in the mediator(s) by imposing specific assumptions (e.g. Heckman and Pinto 2015, Acharya, Blackwell, and Sen 2016, Fagereng, Mogstad, and Ronning 2018, Macmillan and Tominey 2019), or using instrumental variables for the mediators (e.g. Attanasio, Cattan, Fitzsimons, Meghir, and Rubio-Codina 2015 and Aklin and Bayer 2017). In our setting, where we do not have a randomized treatment, we will take into account the endogeneity of both the treatment and mediator using an instrumental variable approach.

Considering an instrumental variable for hours H and another one for income I that do not explain directly the child outcome Y, we could in theory estimate the regression of Y on H and I by using a 2-stage least squares (2SLS) estimation and therefore obtain consistent estimation of the direct effect of H on Y (see Agostinelli and Sorrenti 2018). Nevertheless, such 2SLS estimation does not provide an estimation of the causal relationship between hours H and income I. Therefore it cannot be used to decompose the total effect of hours H on child outcomes Y into the direct and mediator effects.

To consistently estimate the direct and mediator effects, we consider a system of three equations for Y, I and H and we allow the error in each of the equations to be correlated with each other to reflect the endogeneity issues described in Figure 1. The instruments we use for mothers' hours and family income in the pre-school years comes from an application of the partially overlapping peer approach.[5]

In the setting of our paper, parents make decisions about their labour supply in the five years before their first child starts school. This is a period where parents face uncertainty about the returns to their decisions and are likely to be influenced by their peers - other parents of a first child. Indeed, according to Nicoletti, Salvanes, and Tominey (2018), the hours mothers choose to work in their child's pre-school years are influenced by their family and neighbourhood peers. In addition, household income may be affected by peers, through peer effects in consumption (De Giorgi, Frederiksen, and Pistaferri 2015 and Lewbel, Norris, Pendakur, and Qu 2018) and productivity (Cornelissen, Dustmann, and Schönberg 2017) which can drive earnings potential and hours worked of an individual and therefore labour income. We consider parents' "indirect peers", by taking the traits of the peers of parents' peers.

Using Norwegian administrative data we can observe the neighbours, workmates and family members - or the "direct peers" of each household. As is standard practice in the literature, we consider only homogenous peers who had their first child around a similar time and have the same education level as the household. Each neighbour, workmate and family member has their own set of peers which are used to define the indirect peers of a household. The hours (income) of a household will be instrumented with the characteristics of neighbours of the household's family (the workmates of the household's neighbours). To understand the source of variation in the treatment and mediator using this instrumental variables strategy, consider the example of hours. The family's neighbours choose how many hours the mother will work soon after the birth of their first child, these indirect peers choices can influence the hours of the family peers, which, in turn, can affect the household's maternal working hours. The identification assumption is that the influence of the indirect peers on the household is through their direct peers only.

To ensure the validity of our instrumental variables, we make sure (i) to control for endogenous peer group membership; (ii) to avoid reverse causality by considering as instruments parents' peers of peers predetermined characteristics; (iii) that variation in the

[5] See Bramoullé, Djebbari, and Fortin (2009) and Lee, Liu, and Lin (2010) for the theoretical framework and Nicoletti, Salvanes, and Tominey (2018), De Giorgi, Pellizzari, and Radaelli (2015), De Giorgi, Frederiksen, and Pistaferri (2015), Nicoletti and Rabe (2019) for empirical applications.

instrumental variable for household income is independent to the instrument for mothers' hours.

Our main findings suggest that both the direct and mediator effects on school test scores at age 11 and 15 are large in magnitude and statistically different from zero at standard level of 5 and even 1%. As expected the direct effect of an increase in mother's work hours is negative and suggests that mothers time is more productive than the counterfactual childcare. Is it possible to interpret a negative coefficient on mothers' working hours in the test score equations as evidence of a negative effect on children? The answer is no. The income mediator effect is positive and compensates fully for the negative direct effect leading to a total effect that is not statistically different from zero.

When allowing for differential effects across child gender, interestingly, both the direct and the mediator effects of an increase in work hours are larger in magnitude for boys than girls suggesting that boys are more sensitive than girls to changes in time and monetary investments during childhood. There are several other studies that have found that boys are more sensitive to inputs during childhood, e.g. Brook-Gunn et al. (2002), Weitoft et al. (2003), Gayle et al. (2012), Bertrand and Pan (2013), Conti, Heckman and Pinto (2015), Fan, Fang and Markussen (2015), Autor et al (2016). However, the direct and mediator effects cancel out each other for both boys and girls leading to a total effect that is statistically significant neither for girls nor for boys. When we allow the productivity of time and monetary investments in children to vary across mothers' human capital (see Almond and Currie 2011) by stratifying the analysis by mothers' degree status, we do not find significant differences except for a larger mediator effect of income, which is mainly driven by a higher income return to work hours for mother with a degree. Again, for children in low and high educated households, the total effect is not statistically different to zero.

2 Methodology

We are interested in estimating the causal effect on the academic achievements of first born children of mothers' working hours in the preschool period. We measure the academic achievements using school test scores observed at ages 11 and 15. Our aim is to estimate the total average causal effect of mothers hours and to decompose it into the direct effect and the mediator effect through household income.

Let us write the equations for the child school test score, Y, measured at age 11 or 15; mothers' working hours, H; and household income, I, both measured as averages over the preschool period:

$$\begin{aligned} Y &= \gamma_0^Y + H\gamma_H^Y + I\gamma_I^Y + \mathbf{X}\boldsymbol{\beta}^Y + u^Y, \\ I &= \gamma_0^I + H\gamma_H^I + \mathbf{X}\boldsymbol{\beta}^I + \mathbf{Z}^I\boldsymbol{\rho}^I + u^I, \\ H &= \gamma_0^H + \mathbf{X}\boldsymbol{\beta}^H + \mathbf{Z}^H\boldsymbol{\rho}^H + u^H; \end{aligned} \tag{1}$$

where the coefficients have over-scripts to denote the specific equation they refer to, e.g., γ_0^k is the intercept for equation k, with $k = Y, I$ and H, and under-scripts to denote the corresponding explanatory variable. Therefore, γ_H^k is the coefficient for the mother's work hours H in the equation for child academic achievement when $k = Y$, and for household income when $k = I$; γ_I^Y is the coefficient for household income I in the equation for Y. $\boldsymbol{\beta}^k$ is a vector of coefficients in equation k corresponding to the vector of predetermined family and child characteristics, $\mathbf{X}$, which includes child birth weight and child birth weight squared, child gender, mothers' age at birth, mother and fathers' education, parents' labour participation before the first child birth, fathers' income in the year before birth and child month of birth and year of birth dummies;[6] $\mathbf{Z}^k$ is a vector of instrumental variables and $\boldsymbol{\rho}^k$ is the corresponding vector of coefficients; and u^Y, u^I and u^H are error terms. Table A.1 lists the variables included in each of the equations. To ease the interpretation of the coefficients of model (1), we de-meaned H, I and S and standardized the child test score Y within the population by the child birth cohort, to have a mean 0 and standard deviation of 1.

Using terminology from the treatment evaluation and mediation analysis, mothers' work hours H is the treatment, the household income I is the mediator and Y is the outcome. In Figure 1 panels A and B we show a conceptual representation of direct effect captured by the curved arrow going from H to Y, and the mediator effect of H on Y through I represented by the two horizonal arrows.

We are interested in evaluating the average effect of increasing the mothers' hours from a pre-treatment level (denoted by h_0) to a post-treatment level (denoted by h_1), on children's

[6] $\mathbf{X}$ contains also individual instrumental variables which we include to make sure that the exclusion restrictions for the instrumental variables be valid (see Section 2.1 for more details on instruments and individual instruments).

school test scores, Y. This effect is called the average total effect in the decomposition literature and the average treatment effect (ATE) in the casual treatment literature. Such effect can be denoted as

$$E(Y_{h_1} - Y_{h_0}) = E(Y_{h_1,I_{h_1}} - Y_{h_0,I_{h_0}}), \tag{2}$$

where Y_{h_1}, Y_{h_0}, I_{h_1} and I_{h_0} denote the outcome and mediator when treatment H is set at the pre- and post- treatment levels h_1 and h_0. The ATE in equation (2) represents the mean change in test score outcomes when hours change from h_0 to h_1, which in turn raises income from I_{h_0} to I_{h_1} and can be decomposed in the following two additive effects:

1. the *direct effect* of mothers' work hours,

$$E(Y_{h_1,I_{h_0}} - Y_{h_0,I_{h_0}}), \tag{3}$$

   which is the effect of increasing hours from h_0 to h_1 while removing the mediator effect, i.e. keeping the income fixed at I_{h_0};

2. the *mediator effect* of mothers' work hours through household income,

$$E(Y_{h_0,I_{h_1}} - Y_{h_0,I_{h_0}}), \tag{4}$$

   i.e. the effect which is mediated by the change in income from I_{h_0} to I_{h_1} whilst keeping hours at h_0.[7]

We can rewrite the expressions (3)-(4) by using the equations for Y and I in the system of equations (1). By replacing the two outcomes in the direct effect $E(Y_{h_1,I_{h_0}} - Y_{h_0,I_{h_0}})$ with the right hand side of the first equation in (1) and fixing the variables H and I at the corresponding values, we obtain

$$E(Y_{h_1,I_{h_0}} - Y_{h_0,I_{h_0}}) = (h_1 - h_0)\gamma_H^Y, \tag{5}$$

The mediator effect (4) can be rewritten by replacing Y and I with the right hand side of the first and second equations in (1) and fixing the variables H and I at the values denoted in the subscripts,

$$E(Y_{h_0,I_{h_1}} - Y_{h_0,I_{h_0}}) = (h_1 - h_0)\gamma_H^I\gamma_I^Y. \tag{6}$$

[7] For decomposition in the direct and indirect (mediator) effect see also Imai, Keele, Tingley, and Yamamoto (2011), Pearl (2012) and Heckman, Pinto, and Savelyev (2013). The direct and mediator effects are also known as the pure or natural direct and indirect effects (see VanderWeele 2013, VanderWeele 2016).

Notice that the mediator effect is given by the change in income caused by the increase in mother's hours on income, i.e. the product of $(h_1 - h_0)$ and the causal effect of mothers' hours on household income γ_H^I, multiplied by the effect of household income on child test scores γ_I^Y.

The estimation of the direct and mediator effects requires a consistent estimation of the parameters γ_H^Y and γ_I^Y in the outcome equation and of the parameter γ_H^I in the income equation. This implies that we have to deal with the issue of potential endogeneity of the treatment H and mediator I in the outcome equation and of treatment H in the income equation. The endogeneity of H (I) in the outcome equation arrives when there is correlation between the error terms u^H (u^I) and u^Y (see Panel A in Figure 1). This correlation can be caused by unobservable variables which explain both H (I) and Y. Similarly, the endogeneity of H in the income equation arrives if there is correlation between u^H and u^I (see Panel B in Figure 1). We take account of these endogeneity issues by using instrumental variable estimation and we discuss the validity our instruments in Section 2.2.

While there are many studies in different disciplines that have computed the decomposition of the total effect of treatment into the direct and mediator effects without addressing these endogeneity issues; there are also several studies that have solved the issue of endogeneity of the treatment by considering experimental data such as randomized trials interventions (see e.g. Heckman et al., 2013 and 2015). In such randomized interventions, the treatment is exogenous (or exogenous conditional on some observed pre-treatment variables) and therefore there are no unobservables which affect the treatment as well as the mediator and outcome, conditional on some observed pre-treatment variables. In our Figure 1 panel A such exogeneity of the treatment would imply that there are no arrows going from the unobservable u^H to I and Y. Nevertheless, the exogeneity of a randomized treatment does not guarantee that the mediator is exogenous for the outcome Y. This implies that the estimation of the outcome equation using an exogenous treatment H still requires to take account of the endogeneity of the mediator I, i.e. of the fact that there can be unobservables u^I that affect both I and Y (Figure 1 Panel B). Without taking account of such endogeneity issues, the estimation of the total effect of the treatment and its direct and mediator effects will be biased and inconsistent (see e.g. Rosenbaum 1984; Angrist and Pischke 2008; Bullock, Green, and Ha 2010). Some papers have defined specific assumptions under which it is still possible to estimate consistently the direct effect $[(h_1 - h_0)\gamma_H^Y]$ (see Robins 2003, Acharya, Blackwell, and Sen 2016) or both the direct and mediator effects (see Imai, Keele, Tingley, and Yamamoto 2011 and Heckman and Pinto 2015). The credibility of these assumptions is contentious and depends on the empirical application.

In this paper we avoid to impose such assumptions by relying on instrumental variable estimation to solve both the endogeneity of the mediator, I, and of the treatment, H (see also Aklin and Bayer 2017). The mothers' work hours and the household income after the birth of a first child are likely to be affected by peers. This is because new parents are likely to imitate peers or look at peers for information on the effect of work hours and income on their child. Exploiting that parents' peers of peers can affect parents only through the parents' peers, we use the characteristics of peers of peers as instruments for the mothers' work hours and household income (see for more details on these instruments the following section).

We adopt these peers' of peers' instrumental variables to implement a three-stage least squares estimation (3SLS). The first stage consists in the estimation of the reduced form of model (1), i.e. the regression of all endogenous variables on all exogenous explanatory variables and the instruments for mother's work hours and household income. The second stage consists in the estimation of the structural model (1) by replacing the endogenous variables in the right hand side with their predictions from the first stage. Finally, the third stages uses the residuals from the second stage to estimate the matrix of variances and covariances for the error terms and to apply a feasible generalized least squares estimation of the structural model (1).

2.1 Description of our instrumental variables

The two endogenous variables of our model are the mothers' hours and household income in the pre-school years of the first child's life. As anticipated in the last section, we instrument these parental endogenous variables by using average characteristics for parents' peers of peers (indirect peers) that affect directly the maternal hours and household income of the parents' direct peers' and, through these direct peers, affect indirectly the maternal hours and household income of the parents. In the following we define the peers, explain why we expect parents' peers to affect mother's hours and parents income and we provide details on the definition of the instruments.

We consider different types of peer groups: (1) mother's family peers, (2) father's workmates peers, (3) neighbours. We then consider the indirect peers, i.e. the peers of the peers, to derive instruments. The traits of an indirect peer group may be an invalid instrument if the timing of births is such that the household had their child first followed by the child birth of their direct peers and finally by their indirect peers. This scenario can create reverse causation in the regressions on the endogenous variables on the instruments because, for example, the hours and income of the household may influence the decisions of the direct peers, which in turns influences the decisions of the indirect peers. To ensure the instrumental variables are valid, potential peers of a household are defined to be a peer only if they gave birth to their first child before the focal household. In other words, the indirect peers give birth to their first child before the peers, who give birth before the focal mother. Therefore, the instrumental variable measures a decision of the indirect peer group which is made before the household in question has a child.

Given this, we define mother's family peers as her sisters and sister-in-laws who are already mothers. Father's workmates are defined as people working in the same plant as the father, with a first child born between 1 and 5 years earlier, and with the same level of education defined as having a degree or not.[8] Similarly, neighbours are people living in the same postcode, with a first child born between 1 and 5 years earlier, and with the same education.

Both mothers' work hours and household income depend on parents' decisions that can be affected by peers. While mothers can directly decide how many hours to work; income, which in our application is given by the sum of maternal and paternal earnings averaged across pre-school years, depends indirectly on work decisions of the mother and father and on their productivity (or wage) in the labour market. Parents' labour market decisions are made with uncertainty about the return to the inputs on their children. Economic evidence suggests that when parents choose levels of labour market supply during a period of uncertainty, they look to their peers to help inform the decisions or they imitate their peers.

[8]Note, we consider fathers' workmate peers only to avoid any sample selection of mothers into work.

Informed by previous papers on peer effects on women labour supply decisions (see Maurin and Moschion 2004; Mota and Rosenthal 2016; Olivetti 2016; and Nicoletti, Salvanes, and Tominey 2018), which provide clear evidence that both neighbours and family peers affect women's labour decisions, we select the mother's family's neighbours as her indirect peers and use as instrument for the mother's work hours the average maternal work hours of her family's neighbours.

Regarding household income, our model estimates the effect of household income controlling for mothers' labour hours, hence the variation will come mostly from labour market decisions fathers make in the pre-school years. Whilst households cannot directly choose their wage in the labour market, household income can respond to peers through changes in their labour supply, e.g. fathers can decide to increase their working hours if they observe that their peers have costly consumption habits and they decide to conform to these habits. Indeed, De Giorgi, Frederiksen, and Pistaferri (2015) estimated strong effects of consumption choices of neighbours on own consumption. Furthermore, because there can be peer effects in productivity at work (Cornelissen, Dustmann, and Schönberg 2017), we can expect the labour income of the father's workmates to affect his labour income also through his wage and not just through work hours. Given this previous evidence, the labour income of fathers is potentially influenced by their workmates and neighbours through the channels of consumption and productivity choices. In our estimation we use as indirect peers the father's neighbour's workmates. As the workmate peers refer to the workmates of the father, they are less likely to influence the mothers' working hours compared to the fathers' work decisions and labour income. Therefore we instrument household income using the average paternal labour income of neighbour's workmates, which can predict household income independently from the instrument for mother's work hours, i.e. the average maternal work hours of the family's neighbours.

Let $\overline{H}^F$ and $\overline{I}^N$ be the mother's hours and household income averaged across the direct peers of type F, mother's family members, and of type N, father's neighbours.[9] Let $\overline{H}^{FN}$ and $\overline{I}^{NW}$ be the average mother's hours and household income averaged across the indirect peers, which are the mother's family's neighbours (denoted FN) and the father's neighbours' workmates (denoted NW) respectively.

[9]The average across peers are computed excluding the parents in question.

To avoid any endogeneity issue and in particular the reverse causality problem, rather than using directly $\overline{H}^{FN}$ and $\overline{I}^{NW}$ as instruments for H and I, we consider the average across indirect peers of characteristics which predict $\overline{H}^{FN}$ and $\overline{I}^{NW}$, denoted $\overline{Z}_H^{FN}$ and $\overline{Z}_I^{NW}$, which are observed before the mother's hours H and household income I. More precisely, we instrument mother's hours in the pre-school years with the maternal work hours 1 year after the first child birth averaged across the mother's family's neighbours who gave birth to their first child at least 1 year before the mother. We instrument household income in the pre-school years with the paternal earnings 1 year after the first child birth averaged across the father's neighbours' workmates who had their first child at least 1 year before the father.

2.2 Validity of instrumental variables

To be valid instruments, $\overline{Z}_H^{FN}$ and $\overline{Z}_I^{NW}$ must satisfy the relevance and exclusion restrictions. They must be relevant to explain H and I respectively conditional on the control variables, $\overline{Z}_H^{FN}$ must have zero correlation with the error terms u^I and u^Y in the equations for the household income I and the child's outcome Y and $\overline{Z}_I^{NW}$ must have zero correlation with the error term u^Y. We consider each of these assumptions in turn.

In Figure 2 panel A we describe the relevance condition for the instrument for mother's work hours through the causal pathway represented by the two horizontal arrows going from the instrument $\overline{Z}_H^{FN}$ to $\overline{H}^F$, the average of H across direct family members, and from $\overline{H}^F$ to the mother's hours, H. The relevance condition is satisfied because the instrument for hours $\overline{Z}_H^{FN}$ is a predictor of the average of H across family's neighbours, $\overline{H}^{FN}$, which affects the mother's hours through the channel of the direct family peers decisions, $\overline{H}^F$. Similarly, in Figure 2 panel B $\overline{Z}_I^{NW}$ is relevant because of the causal pathway represented by the two horizonal arrows from $\overline{Z}_I^{NW}$ to $\overline{I}^N$, the average of income across direct neighbours, and from $\overline{I}^N$ to I. Our regression analysis includes the relevant statistics to confirm that our instrumental variables are strong predictors of hours and income respectively.

Next, we consider the exclusion restrictions from the child test score (Y) equation, i.e. the assumption that correlation between the instrument for H and u^Y and between the instrument for I and u^Y must be zero. The zero correlation between $\overline{Z}_H^{FN}$ and u^Y is satisfied if there is no effect going from the peers of peers, the family's neighbours, to the child test score, Y, except through the mother's hours H. Similarly, the zero correlation between $\overline{Z}_I^{NW}$

and u^Y is satisfied if there is no effect going from the neighbours' workmates to the child test score, Y, except through the household income I.

There are only two threats to these exclusion restrictions which are described graphically in Figure 2 by the pathways from the instrument ($\overline{Z}_H^{FN}$ in panel A and $\overline{Z}_I^{NW}$ in panel B) to the child's test score Y that are not going through H and I.

The first threat to the validity of the instrument for H, $\overline{Z}_H^{FN}$, is caused by the fact that the average of H across the parents' direct family peers, $\overline{H}^F$, can affect the average test score of the children of these direct peers, $\overline{Y}^F$, which in turn can affect the child's test score Y (see the pathway from $\overline{Z}_H^{FN}$ to Y going through $\overline{Y}^F$, in panel A of Figure 2). This is because, if H affects Y, then the average of H over the family peers, $\overline{H}^F$, must affect the average of Y over the family peers, $\overline{Y}^F$, which can ultimately have a spillover effect on the child test score Y. Looking at panel A of Figure 2, it is then evident that there is a pathway going from the instrument $\overline{Z}_H^{FN}$ to the child's test score Y through $\overline{Y}^F$, which does not pass through H. To avoid this threat to the validity of our instrument, in our estimation we include $\overline{Y}^F$ among the vector of controls $\mathbf{X}$ in all equations in the system (1). The corresponding threat for the validity of the instrument for I, $\overline{Z}_I^{NW}$, is described in panel B of Figure 2 by the pathway going from $\overline{Z}_I^{NW}$ to the child test score Y through $\overline{I}^N$ and $\overline{Y}^N$. Similarly, we take account of this issue by including $\overline{Y}^N$ among the vector of controls $\mathbf{X}$ in our system of equations (1).

The second threat to the validity of our instruments is the endogeneous peer membership. Endogenous peer membership exists if individuals sort into their peer groups based in part on unobservable traits which may also explain our outcome of interest, the child's test score. In particular we are concerned that parents' family peers can sort out into neighbours with unobserved characteristics that are similar to the parents' direct neighbours. If this is the case, then we could have a correlation between the instrument for hours, $\overline{Z}_H^{FN}$, and $\overline{Z}_H^N$, i.e. the average of Z across the parents' direct neighbours. This correlation is represented by the double pointed arrow between $\overline{Z}_H^{FN}$ and $\overline{Z}_H^N$ in panel A of Figure 2. Because $\overline{Z}_H^N$ predicts the neighbours' average hours $\overline{H}^N$ that can affect $\overline{Y}^N$ and ultimately the child's test score Y, we have a second pathway from the instrument $\overline{Z}_H^{FN}$ to the child's test score that is not passing through H and therefore can invalidate our instrument (see the pathway from $\overline{Z}_H^{FN}$ to Y through $\overline{Z}_H^N$ in panel A). A solution suggested by Bramoullé, Djebbari, and Fortin (2009) for the endogenous peer membership is to control for a network fixed effect. However as pointed out by Caeyers and Fafchamps (2016) this will induce an "exclusion bias" in the estimation as the fixed effect includes the observation for the household in question. Therefore we follow Nicoletti, Salvanes, and Tominey (2018) and Hinke, Leckie, and Nicoletti (2019) by including the "individual instrumental variable" - which is the instrument defined at the level of the individual, i.e. we include $\overline{Z}_H^N$ in the vector of controls $\mathbf{X}$ in all our equations. Similarly, to avoid the bias caused by the sorting out of fathers into a workplace that could be similar to their neighbours' workplace, i.e. the bias caused by the correlation between $\overline{Z}_I^{NW}$ and $\overline{Z}_I^W$ (see double pointed arrow in the top left side of panel B in Figure 2), we include $\overline{Z}_I^W$ among the controls in all our equations.

We have so far considered the exclusion restrictions from the child's test score equation and now move to consider the corresponding exclusion restrictions from the income equation, i.e. the assumption that the instrument for hours, $\overline{Z}_H^{FN}$, must have zero correlation with the error term of the income equation, u^I. The identification assumption of zero correlation is satisfied if there is no effect going from $\overline{Z}_H^{FN}$ to I, except through the mother's hours H. In Figure A.1, we show there is a pathway going from the instrument for hours, $\overline{Z}_H^{FN}$, to the household income, I, which does not pass through mother's hours H and is therefore a potential threat to the validity of the instrument $\overline{Z}_H^{FN}$. This threat is caused again by the potential sorting of parents family peers in neighbourhoods with unobserved characteristics that are similar to the parents' neighbourhood (see the pathway from the $\overline{Z}_H^{FN}$ to I through $\overline{Z}_H^N$ in Figure 3). Nevertheless, because we include among the control variables in all our equations the $\overline{Z}_H^N$, this threat disappears. We assume that fathers' earnings are not affected by changes in mothers' work hours in their family (in their sisters and sisters-in-law), $\overline{H}^F$, except through their own partner (mother) changes in hours. For this reason $\overline{H}^F$ can affect Y only through H.

3 Data

We use Norwegian registry data, collected by different administrative units, and linked by Statistics Norway. The data combines information from different registers across time and provide details on children's school test scores, their parental income, education and employment and information to identify where people live, work, and who their family members are. Our analysis focuses on first born children, for the reason that parental investments for the second child can react to changes in the endowments of the first child, a mechanism that we want to rule out in our analysis. For example if the mother returned to work early after having a first child and observed a fall in the child's test scores, they may delay the return for the second child. Each child is linked to their parents using the birth registry, where we also identify first born children.

For parents the annual labour market participation status, hours worked and earnings is recorded in all pre-school years and is based on the tax statistics. The yearly household income in each of the pre-school years is defined as the sum of the mother's and father's yearly net income (labour earnings), deflated to the year 2000. Net income is calculated as the gross income received, net of any taxes and transfers. These transfers include a progressive income tax, child benefits for children up to age 18, unemployment and sickness benefits and any other cash transfers from the social insurance system, general deductions for work related expenditures and finally a regional compensation for living in the Northern most region of Norway. In a particular year, weekly hours worked is defined from a discrete variable taking the value of 0, 1-19, 20-29 and 30+ hours. A continuous variable is constructed by taking the mid-point of each category, whereby hours is defined as 0, 10, 24.5 and 40 (where 40 hours is equivalent to a full-time contract in Norway).

The pre-school labour market household income and hours worked are constructed as the mean values between 1 and 5 years after the first child was born of the above defined weekly hours and yearly household income. The mean value of household income and mothers' labour hours in pre-school years are approximately 350,000 Kroner and 20 hours, reported in Table 1.

Age 11 test scores are recorded for the population of children born between 1997-2005, whereas the age 15 test scores exist in the education statistics for birth cohorts 1996-2001. We select a common sample across the two outcomes, choosing cohorts born between 1997-2001. Both test score outcomes are constructed by summing grades on Maths and Reading.[10] The test scores at age 11 and 15 are not high stake for the child and therefore more likely to represent child ability as opposed to school quality if schools "teach to the test." The

[10] We repeated the analysis separately for maths and reading test score outcomes and found no difference to our benchmark. The results are available on request.

descriptives in Table 1 report the mean and standard deviation of all variables used in our analysis. Test scores at ages 11 and 15 have a mean of 47 and 66 respectively. In our analysis we standardise the test score within the population to have a mean of zero and standard deviation of 1, within each cohort.

From the education statistics and labor market statistics we also derive details on parents' characteristics observed before the birth of their first child, which we use as control variables. In Table 1 we report descriptives for these pre-birth parental variables, which include parents' education (mothers and fathers have on average 13 years of schooling and around 50% of mothers have a degree), mothers' age at birth (26.5 on average) and labour market variables for the parents, including a dummy variable indicating mothers' and fathers' working status in the year before birth (77% of mothers and 97% of fathers work in the year before birth) and fathers' net income in the year before birth. We also control for the child year of birth and a quadratic specification of child birth weight, measured from the birth registry.

Crucial for our identification strategy is the definition of peer groups and we construct the neighbourhood, workmate and the family peer group in a similar way to Nicoletti, Salvanes, and Tominey (2018). We are able to construct these peer groups using the population, the employer-employee and the population registers to identify where people live, the plant where they work and their family connections and to define three corresponding sets of homogenous (relevant) peers which are the neighbourhood, workplace and family peers. We define the mother's neighbours as women living within the same postcode and with same level of education (defined by degree status of mothers) and who gave birth to their first child between one and five years before the focal mother. There are around 2,500 households on average in a neighbourhood and, the relevant neighbourhood peer group consists of a much smaller number of households of around 63 neighbours.

Workmate peers are defined for the father to avoid the issue of selection into employment. The issue is most important for mothers; 70% of whom work in the years after child birth compared to around 97% of fathers. A workmate is defined as an individual working in the same company at the same location as the father, who had their first child between 1-5 years before the father and with the same degree status. A father has on average 16 workmate peers. Finally, the family peer group is constructed from all sisters and sister-in-laws who gave birth before the household of interest had their first child. Identification of a family peer requires matching for each parent in our data an identifier for their own parents (i.e. the grandparents of the children for whom we observe school test score outcomes) using data on the census dating back to 1967. Families have on average 2.4 sisters or sister in laws. Similarly to the definition of the other two peer groups, an individual can only be a classed as a peer if they gave birth before the mother in question and has the same degree status.

The instrumental variable (IV) for income is the paternal earnings average across the neighbour's workmates of the focal father; and for hours is the mothers' hours worked average across the family's neighbourhood peers of the focal mother. Table 1 reports additionally the descriptive statistics for the "individual IVs" which are the controls necessary to identify the causal effect of mothers' work hours and family income on child outcomes as discussed in Section 2.2.

4 Results

4.1 Regression Results

We estimate the above set of equations (1) for the child's test score Y using 3SLS. The estimation results for the Y equation are reported in the top panel of Table 2 where we focus on the effects of two parental pre-school inputs, mothers' hours and household income. Columns (1) and (2) report results for the school test score measured at age 11 and 15 for the full sample of children. All regressions include the set of controls detailed in Table A.1.

First to note in Table 2 is a negative and statistically significant coefficient on mothers' hours worked on child test score outcomes, across both ages 11 and 15. An increase in mothers' hours worked by 1 per week in each of the five pre-school years translates into a reduction of test scores at age 11 and 15 by 3.6% and 3.0% of a standard deviation. The coefficient on mothers' hours indicates the productivity of the mothers' time relative to time spent with the alternative, for example time with a father, a grandparent, with a nanny or in formal childcare. In Norway by far the most common childcare provision when parents work is a formal childcare provider. The result suggests that the mothers' time is more productive than the counterfactual childcare.

Second to note is that across ages 11 and 15, income is strongly predictive of child test scores. At age 11 and 15, an increase in household income in the pre-school years of the first child by NOK100,000 (approximately 11,000 US dollars and two thirds of a standard deviation) raises test scores by 26.3% and 25.0% of a standard deviation respectively. Strikingly, the effects of income on child test scores are similar at ages 11 and 15 meaning that there is no fade-out of the productivity of early parental income on child outcomes between ages 11 and 15. This finding is similar to Carneiro, Garcia, Salvanes, and Tominey (2015) who find that the productivity of early life family income raises child outcomes up to 30 years later.

The bottom of Table 2 reports the first stage statistics. Looking at the two first columns, the IVs for income and hours are strong and statistically significant predictors of the variables income and hours with F-statistics equal to 312 and 39 for income and hours respectively. Moreover the p-values of two endogeneity tests are reported - the test relating to the endogeneity of income and hours variables in the test score equation and the test of endogeneity of hours in the income equation. The p-values are zero suggesting that the main regressors of income and hours are endogenous. Indeed in Table A.3 we report the OLS estimation results for the equations for the test score at age 11 and 15. As expected, the results are remarkably different to our benchmark estimates of Table 2. For example in all samples the coefficient of hours on test scores at ages 11 and 15 is positive and significant, whereas in Table 2 the coefficient on hours was negative and the coefficients on income in the OLS regressions are lower than in our benchmark regressions. This suggests there is a need to control for endogeneity of household income and mothers' working hours in the equation for test scores at both age 11 and 15.

Table A.2 reports the full set of coefficients for our benchmark specification.

4.2 Decomposition analysis

Is it possible to interpret a negative coefficient of mothers' working hours in the test score equations as evidence of a negative effect on children? In order to answer this question we progress to decompose the total effect of a change in mothers' labour hours from h_0 to h_1 into the direct effect and the mediator effect defined in equations (5)-(6). Our benchmark decomposition results in Table 3 considers a relatively large change in mothers' working hours of 10 hours per week. Columns (1) and (2) of Table 3 report results for the age 11 and age 15 test score outcomes respectively for the full sample of children.

The direct effect of an increase in mothers' hours, holding constant any changes in income in Table 3 is the coefficient on hours from Table 2, scaled up to represent a 10 hour change, which is negative and statistically different to zero.

Of course, a change in mothers' labour hours will raise household income. Evidence has suggested that household income causally raises child outcomes[11] hence can potentially mediate or compensate for the negative direct effect of mothers' working hours by, for example, raising monetary investments in children. Columns (1) and (2) report the mediator effect from an increase by 10 in mothers' working hours at ages 11 and 15, which is given by the product of the effect of 10 hours increase on income, $(10\gamma_H^I)$, and the effect of income on the child test score, γ_I^Y. The mediator effect at both ages is positive and statistically significant. The increase in income associated with the increase in mothers' labour hours by 10 per week, whilst removing the direct effect of the change in mothers' hours, leads to an increase in test scores at age 11 and 15 by 40.7% and 38.7% of a standard deviation respectively.

Can income compensate for a reduction of mothers' hours in pre-school years? The answer is yes. In columns (1) and (2), the positive mediator effect is always larger than the negative direct effect, hence the total effect of an increase in mothers' pre-school hours on child outcomes is positive, although not statistically distinguishable from zero.

To illustrate the contribution of the direct and mediator effect to the total effect of the change in mothers' hours, Figure 3 plots out the distribution of test scores at ages 11 (panel a) and 15 (panel b). The figure shows the original distribution pre-treatment (labelled "Original") and the shift in the distribution from the direct, mediator and total effects. In both plots at age 11 and 15 (see top and bottom panels in Figure 3) the total effect shifts very little compared to the original distribution of test scores, as expected from the decomposition analysis. The direct effect of a reduction in the mothers' time investments shifts the distribution of test score outcomes to the left, but this is fully compensated for by the mediator effect, which shifts the distribution right.

[11] See for example Dahl and Lochner (2012).

Fathers enter our analysis through the effect of household income and because the mediator effect captures any behavioural response of fathers' earnings to an increase in mothers' hours. Recall the mediator effect is the product of the effect of household income on child test scores and the effect of hours on household income, both reported in Table 2. Notice that the household income, I, is given by the sum of father's and mother's yearly earnings, $I = (E^F + E^M)$, so the effect of an increase in mother's work hours is given by

$$\gamma_H^I = \frac{\partial I}{\partial H} = \frac{\partial E^M}{\partial H} + \frac{\partial E^F}{\partial H}, \tag{7}$$

where E^M and E^F are the mother's and father's average yearly earnings between age 1 and 5, $\frac{\partial E^F}{\partial H}$ is the father's earnings marginal response to an increase in mother's hours and $\frac{\partial E^M}{\partial H}$ is the marginal effect of an increase in mother's hours on mother's earnings, i.e. the mother's wage rate.

To summarize, despite a negative coefficient on hours in all test score equations at 11 and 15, the total effect of an increase in mothers' pre-school hours is always close to zero and instatistically different to zero.

4.3 Heterogeneity analysis by gender

There is growing evidence that the production function relating parental investments to child outcomes is different for boys than for girls. For example Autor, Figlio, Karbownik, Roth, and Wasserman (2016) find that boys respond to a greater extent to high quality schooling than girls, Bertrand and Pan (2013) document how boys' socio-emotional skills are more sensitive to parental divorce and Fan, Fang, and Markussen (2015) find that the effect of early life maternal employment is to reduce the probability of attaining a degree later in life and this effect is stronger for boys than girls.

In line with this evidence, our analysis next stratifies the sample by the child's gender to explore whether it is true for both sexes that income compensates for the negative effect of mothers' labour hours.

The regression estimates and decomposition results are reported in columns (3)-(6) Tables 2 and 3 respectively. Consistent with the existing literature, our analysis suggests that girls are less sensitive to a change in parental inputs than boys. In particular, in Table 2 we find that the effect of mothers' hours on the test score outcomes of girls, although negative, is not statistically significant. On the other hand, an increase in mothers' weekly labour hours lowers the outcomes of boys at ages 11 and 15 by 5.4% and 3.8% of a standard deviation respectively, and these estimates are statistically different to zero.

Similarly, the productivity of pre-school household income is more than double for boys compared to girls. The effect of an increase in NOK100,000 raises test scores at age 15 by 34.6% and 15.0% of a standard deviation for boys and girls respectively.

Moving to the decomposition analysis results in Table 3, columns (3) and (5) report results for girls at ages 11 and 15; whilst columns (4) and (6) report results for boys at ages 11 and 15. The total effect of an increase in mothers' hours by 10 per week for each pre-school year has a zero effect on test scores at ages 11 and 15 for both girls and boys. Figure A.2 reports the same results but illustrated by the plots of the density of the test scores with no changes (labelled original), the density shifted by the direct effect (labelled direct effect), the density shifted by the mediator effect (labelled mediator effect) and finally the density shifted by the total effect of an increase by 10 in the mother's hours worked (labelled total effect). Panels a) and b) show that for girls the direct effect of a change in mothers' working hours shifts the distribution of test score at ages 11 and 15 towards the left slightly, while the mediator effect mitigates for such negative direct effect by shifting the distribution slightly to the right so that the density shifted by the total effect is undistinguishable from the original density. For boys, the direct and mediator effects are substantially larger compared to girls and cause a substantial shift in the densities of the test scores at age 11 and 15, but again any negative effect of a reduction mothers' time investments in pre-school years is compensated for by the associated increase in income and the original test score density is almost identical to the density shifted by the total effect. Therefore our summary is that for boys and girls, income fully compensates for any negative effect of a reduction in mothers' time associated with an increase in her pre-school working hours.

To see whether the increased sensitivity of boys to pre-school family inputs is driven boys at the bottom or top of the distribution of child ability, we estimate an unconditional quantile regression model (see Firpo, Fortin, and Lemieux 2009), allowing the effect of inputs to vary across the deciles of child test scores. Figure A.3 shows the shifts in the density of test scores caused by an increase of mothers' work hours by 10 and distinguishing between the direct effect, the mediator effect through income and the total effect. The distributions have been smoothed by plotting a kernel density distribution with a bandwidth equal to one. For boys, the direct and mediator effects shift the original distribution of test score outcomes to the left and right by a value which is almost constant across the distribution of boys' skills at both age 11 and 15 and lead to total effect density which almost perfectly overlay the original density. For girls on the other hand, there is some evidence that the total effect is slightly more negative when girls are at the bottom of the test score distribution at age 15 and slightly more positive or when they are at the top of the distribution at age 11.

4.4 Heterogeneity analysis by mothers' education

Almond and Currie (2011) and Heckman and Mosso (2014), suggest that economic modelling of the effect of parental inputs on child outcomes should allow for a different productivity by the human capital of parents. Indeed, there is evidence that the return to pre-school education varies by parental education (see e.g Cornelissen, Dustmann, Raute, and Schönberg 2018). For this reason, next we consider heterogeneity in the analysis by the education level of the mother.

The direct effect reflects the relative productivity of time at home with the mother versus the productivity of time in child care. This may vary across mothers' education for three reasons. Firstly if the quality of the child care provision is heterogeneous across socio-economic status such that for example high educated households send children to a higher quality of care then the negative direct effect will be smaller for higher educated mothers. However in Norway all mothers access a relatively homogenous childcare across all preschool settings because of a common curriculum and fees that are income related to ensure equal access for children from low-income families.

Second the quality of mothers' time investments is potentially increasing across the education level of mothers (see e.g. Hill and Stafford 1974; McLanahan 2004; Guryan, Hurst, and Kearney 2008; Dotti Sani and Treas 2016). Kalil, Ryan, and Corey (2012), Kalil (2015) and Dotti Sani and Treas (2016) document a positive parental educational gradient in time investments and quality of child environment at home. If the productivity of time in child care is lower than the productivity of time spent with a highly educated mother, and vice versa for a low educated mother, then we would expect one extra work hour to have a more negative direct effect on child test scores for women with high education.

On the other hand, there is evidence that highly educated mothers protect their quality time investments as they increase their labour supply and in general the time mothers spend in educational or quality activities with their children does not differ across hours worked. If mothers with high education do not diminish the quality time spent with their children as much as mothers with low education, then we could find a more negative effect of an increase of work hours on child's test scores for mothers with low education.

Similarly, the effect of household income on child test scores may vary across mothers' level of education if (i) mothers with low and high education have different preferences for monetary investments in children; (ii) the productivity of monetary investments differs across level of mother's education; (iii) low educated mothers face credit constraints such that an increase in income frees up resources to invest in their children.

We allow for the heterogeneous productivity of parental inputs in Table 4 by stratifying the estimation by the degree status of mothers. Columns (1) and (3) report results for mothers with no degree and columns (2) and (4) for mothers with a degree. For mothers with or without a degree, an increase in mothers' pre-school hours lowers test score outcomes at ages 11 or 15 by between 2.2%-3.4% of a standard deviation. There is no statistically significant difference across the four sets of estimates. This suggests that if it is true that the productivity of mothers' time investments in children are higher for more educated mothers, these mothers also protect quality investments as they raise their labour hours leading to a similar effect of hours on child test scores in the low and high educated households.

In contrast, household income is more productive in the high education households, where an increase of NOK100,000 raises outcomes at age 11 and 15 by 26.3% and 25.7% (19.3% and 15.9%) of standard deviation for mothers with (without) a degree. There are several possible explanations for this and in Section 4.4.1 we ask i) does an increase in income for high educated households leads to more productive investments in child human capital and ii) is income less productive in low educated households due to different life choices made after the child is aged 5, such as incidence of divorce and having more children.

Table 5 reports the decomposition results allowing for heterogeneity by mothers' education. Columns (1) and (3) report results for the sample of mothers with no degree at ages 11 and 15 respectively; and columns (2) and (4) for the sample of mothers with a degree. The total effect of an increase in mothers' pre-school hours worked is not statistically different to zero for both mothers with a high and low education. However, in Table 5 there are large differences in the magnitude of the total effects across the mothers' education. In particular, in low educated households the positive mediator effect does not fully compensate for the negative direct effect, leaving a total effect which is negative. On the other hand, the mediator effect for high educated mothers is more than double the direct effect, leading to a positive total effect. These results are obvious in Figure A.4 which shows a positive total effect in high education households, but a negative total effect in low educated households. As noted, due to the standard errors these total effects are not statistically significant, but the different signs of the total effects may tell us something about how inequalities accumulate across children of different socio-economic status.

The larger mediator effect for well educated mothers comes from two sources. First we saw in Table 4 that income is more productive compared to the lower educated mothers. But secondly, the coefficient on hours in the income equation (γ_H^I) in Table 4 indicates that the household wage is higher for mothers with a degree. The coefficients of 0.216 and 0.102 translate into an hourly wage of NOK200 or \$22 per hour for mothers with a degree and NOK100 or \$11 per hour for mothers with no degree.[12] Therefore the difference in the mediator by mothers' education is due both to a higher productivity of income in high education households and a higher wage.

4.4.1 Explaining heterogeneity by mothers' education

The productivity of household income is higher in households with highly educated mothers according to Table 4. We explore two potential explanations, focusing firstly on whether high educated households spend their money more productively on investments in child human capital. Up to age 16, there is no school choice in Norway and children attend the local

[12]Following equation 7, γ_H^I in Table 4 is adjusted by removing the increase in fathers' income associated with an increase in mothers' hours. The adjustment of fathers' income to an increase in mothers' hours was estimated via a 2SLS estimation instrumenting mothers' hours using our benchmark IV, to be NOK4,985 and NOK11,246 in the low and high education households respectively.

school. Nevertheless, household income can raise child outcomes by enabling parents to buy a house in a neighbourhood with good schools. Does an increase in household income have a stronger association with neighbourhood school quality in high educated households? We re-estimate the model allowing for heterogeneous effects by mothers degree status but change the dependent variable to the mean school quality measured through the test scores at age 11 and 15 averaged across the neighbourhood. The mean school quality is measured across five cohorts before the benchmark child took their examinations and it is standardized to have mean zero and variance one separately at age 11 and age 15.

Table A.4 reports in panel a) the regression estimates for the effect of mothers' pre-school labour hours on school quality measured at age 11 (columns 1 and 2) and 15 (columns 3 and 4) for households in which the mother has no degree (columns 1 and 3) and a degree (columns 2 and 4). Note that the effect of income on the neighbourhood school quality at age 11 and 15 is statistically significant and similar in the low and high educated household. An increase in household income by NOK100,000 raises the neighbourhood school quality by around 20-30% of a standard deviation. The effect of mothers' hours on neighbourhood quality is positive and statistically significant and slightly larger for high educated households. Panel b) of Table A.4 reports the decomposition results of the effect of an increase in mothers' pre-school hours. An increase in mother's hours leads to a positive total effect on neighbourhood school quality that is larger for highly educated mothers. This seems to be driven by both a larger positive direct effect and a larger mediator effect for educated mothers who receive a relatively higher wage that allows them to purchase a home in an area with higher school quality for their children.[13] Both mothers with and without a degree who work longer hours seem to put more effort in choosing neighbours with good quality schools, but mother with a degree seem to be better able to choose the best neighbours when they increase their work hours.

Second, it could be that the productivity of income in the pre-school years is capturing the effect of other inputs. For example, the effect of income may capture the fact that in households with low income and financial pressures, the relationships between parents may be more conflicted and divorce rates higher.[14] As another example, there is a well documented

[13]See Machin and Salvanes (2016) for evidence on the relationship between house prices and quality of schools.

[14]Our main sample considers only intact family during the preschool period, but also disrupted families after the age of 5.

correlation between family income and completed fertility size (see Becker and Lewis (1973) for example). The greater productivity of household income in the high educated households may be picking up a correlation between income in the pre-school years with divorce and fertility up to the age of the test score.

To explore this mechanism, we construct a sample of homogenous households who do not divorce up to age 11[15] and have no more than 3 children by the age of 11. The sample is selected based on endogenous controls but can inform the extent to which our results are driven by the correlation between pre-school inputs and inputs after the age of 5. The regression results are shown panel a) in Table A.5, whilst the decomposition results are reported in panel b). Notice that the sample size has dropped to 57,405 children with 29,253 and 28,152 living in low and high educated households respectively. The results in Table A.5 are very similar to the ones based on the full samples of mothers with and without a degree (see Table 2) and suggest that, even when considering only homogenous households who have no more than three children and do not divorce, a combination of a higher productivity of income with a higher wage rate in the high educated households leads to a larger mediator effect.

5 Sensitivity

5.1 Parental inputs after pre-school years

There is likely to be a high correlation between parental inputs in the 1-5 years after birth of a first child and parental inputs from age 6 onwards. Whilst we may expect household income and mothers' hours to vary year-on-year, the level of the inputs in the pre-school years is highly correlated with inputs from age 6 onwards.

To address a concern that our estimates of the effect of pre-school parental inputs on children may pick up the effect of inputs that occur *after* the child starts school, we estimate the mean household income and mean mothers' hours between years 6-11 and control for each in turn in regressions of test score outcomes at age 11 and 15.[16] These are clearly endogenous

[15] unfortunately our data on marital breakup can not be observed up to when the children are 15 but only to age 11.

[16] Income and hours data is not available past the child's age of 13 in some cohorts, so for simplicity we control for income or hours up to age 11.

controls, but our analysis reported in Table A.6 shows that our results are not statistically different to our benchmark estimates once we condition on income (columns 1 and 2) or hours (columns 3 and 4) after the pre-school years. Moreover, the decomposition analysis shows no statistically significant total effect of mothers' pre-school hours suggesting that our results are robust to removing the influence of income or hours received after pre-school years.

5.2 Non-linearity in the effect of income and hours on test scores

Our benchmark model specification assumed that income and hours affect child test scores linearly. We firstly relax that assumption by including as regressors in the child test score equations at ages 11 and 15 the square of household income and mothers' hours worked. Reported in panel a) of Table A.7, the coefficient for hours squared in the age 11 or 15 test score equations are not statistically significant. On the other hand, in columns (3) and (5), for test score outcomes at age 15, income squared has a negative and statistically significant coefficient. The question is whether this non-linearity in the effect of income translates into different conclusions from the decomposition analysis and panel b) of Table A.7 shows that the decomposition estimates are almost identical to our benchmark.

Next we test for a non-linear effect of hours on test score outcomes in a more flexible specification. It may be that the marginal effect of an increase mothers' working hours on children is very different when comparing mothers moving from a low number of hours, to an increase starting from a higher level of hours. To test this, we use linear regression splines in mothers' working hours, with knots defined at the quartiles of mothers' working hours. Table A.8 reports in panel a) the regression results, where the coefficients represent the marginal effect of hours at a particular quartile relative to the first. In column (1) there is some evidence of a differential effect of hours on test score outcomes at age 11 at quartiles 2-4 compared to quartile 1, however in the decomposition analysis this non-linearity in the effect of hours does not affect our conclusions that the total effects are not statistically different to zero. In column (2), there is neither evidence of a non-linear effect of hours on child test score outcomes at age 15 nor is there any change to our conclusion that the total effect of an increase in mothers' labour hours is zero.

In a similar way, we test for a non-linear effect of income on test score outcomes, by using a linear regression spline across deciles of the income distribution. Column (1) and (2) of Table A.9 reports that at age 11 and 15, there is no non-linearity in the effect of income on child test scores with the exception of one coefficient in column (1). In the decomposition analysis we draw the same conclusions that the total effect of an increase in mothers' labour hours is zero.

Next we test for the presence of an interactive effect of hours and family income on child test scores. The return to household income may change across the distribution of hours or vice versa. Therefore, we consider estimation of test score outcomes to include the interaction term between mother's hours and income in the test score equation, i.e.

$$Y = \gamma_0^{\prime Y} + H\gamma_H^{\prime Y} + I\gamma_I^{\prime Y} + I \cdot H\gamma_{I,H}^{\prime Y} + \mathbf{X}\boldsymbol{\beta}^{\prime Y} + u^{\prime Y} \tag{8}$$

where $\gamma_{IH}^{\prime Y}$ denotes the coefficient on the interaction term between I and H. In Appendix Section A.1 it is made clear that including in the test score equation the interaction between I and H changes the decomposition of the total effect, by changing the direct and indirect effects as well as adding a new component called the "interaction" effect. Reported in Table A.11 are the regression estimates (panel a) and decomposition results (panel b) when including the additional interaction term. The contribution of the interaction effect to the total effect is very small and not statistically significant on the whole. Consequently, including the additional interaction term does not lead to a statistically significant change in the direct, indirect or total effects of mothers' labour hours in pre-school years on outcomes at either age 11 or age 15.

5.3 Validity of model with two endogenous variables

Our model is quite demanding, as it involves two endogenous variables along with two instrumental variables. Estimating the model through a system of equations is necessary to control for the correlation between the error driving hours u^H and income u^I, which are potentially correlated with the error driving the child test score, Y. We argue that there is exogenous variation in income induced by the instrument for income that is independent of the instrument for hours, because the instruments are average characteristics for entirely different sets of indirect peers - the family's neighbours and the neighbour's workmates of fathers.

To reassure ourselves that the complexity of our model does not compromise the estimation results, we check whether the total effect of an increase in mother's work hours estimated using our model with two endogenous variables is similar to the total effect which can be computed using a much simpler model, i.e. the regression of the child test score on the mother's work hours, including all controls from our benchmark but excluding family income. In such simpler model the coefficient for mother's hours captures both the direct and the mediator effect through income and can be estimated consistently by using a 2SLS estimation, i.e. by instrumenting the endogenous mothers' pre-school hours with the same instrumental variable used in our benchmark specification

The coefficient for mother's hours estimated using 2SLS should be equal to the total effect of hours estimated in the decomposition analysis of Table 3, multiplied by 10 because in our decomposition analysis we consider the total effect for an increase of 10 hours. Table A.12 confirms indeed that the total effect of a 1 hour change in mothers' labour hours estimated using 2SLS estimation is identical to the total effect in our benchmark decomposition analysis. Even with a complex system of equations and two endogenous variables, our benchmark specification estimates a total effect of hours on child outcomes which is almost identical to the estimates from a more simple model with just one endogenous variable.

6 Conclusion

Does income compensate for mothers working during preschool years? By using Norwegian administrative data covering the full population of first born children between 1997 and 2001, we decompose the total effect of an increase in mothers' labour hours on children into the causal direct effect through a reduction in her time investments, and the causal mediator income effect. We find that the negative effect of an increase in mothers' hours worked on child outcomes at age 11 is at least partially compensated by the increase in household income, whilst by age 15 is fully compensated.

An increase in mothers' hours worked during preschool years leads to changes in the time allocation of children by replacing the time a mother spends with her child with alternative childcare time. This may create a potential decrease of the total time the child spends in educational, playing and other activities that are important for child development. Such changes in time investments, conditional on household income, cause a decrease in child's test scores at age 11 and 15 by around 30-36% of a standard deviation. However, this negative coefficient on mothers' hours cannot be interpreted as a negative total effect of mothers' working in pre-school hours. The reason is that household income is a mediator to the effect of mothers' hours. An increase in mothers' pre-school hours raises household income which in turn causally raises child test score outcomes. In fact, this mediator effect fully compensates for any reduction in mothers' time investments leading to a total effect of mothers' hours which is essentially zero. Although there are interesting differences in the causal effects of hours and household income on child outcomes across child gender, or across mothers' education, in all cases the total effect of an increase in mothers' hours was not statistically different to zero.

References

Acharya, A., M. Blackwell, and M. Sen (2016): "Explaining causal findings without bias: Detecting and assessing direct effects," *American Political Science Review*, 110(3), 512–529.

Agostinelli, F., and G. Sorrenti (2018): "Money vs . Time : Family Income , Maternal Labor Supply , and Child Development Money vs . Time : Family Income , Maternal Labor Supply , and Child Development," .

Aklin, M., and P. Bayer (2017): "How Can We Estimate the Effectiveness of Institutions? Solving the Post-Treatment versus Omitted Variable Bias Dilemma," .

Almond, D., and J. Currie (2011): "Human Capital Development Before Age Five," *In D. Card and O. Ashenfelter (eds.) Handbook of Labor Economics*, 4(15), 1315–1486.

Angrist, J. D., and J.-S. Pischke (2008): *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Attanasio, O., S. Cattan, E. Fitzsimons, C. Meghir, and M. Rubio-Codina (2015): "Estimating the production function for human capital: Results from a randomized control trial in Colombia," Discussion paper, National Bureau of Economic Research.

Autor, D., D. Figlio, K. Karbownik, J. Roth, and M. Wasserman (2016): "School quality and the gender gap in educational achievement," *American Economic Review*, 106(5), 289–95.

Baker, Michael, G. J., and K. Milligan (2008): "The Effect of Maternal Employment and Child Care on Children's Cognitive Development," *Journal of Political Economy*, 116(4), 709–745.

Baker, M., and K. Milligan (2015): "Maternity leave and children's cognitive and behavioral development," *Journal of Population Economics*, 28(2), 373–391.

Becker, G. S., and H. G. Lewis (1973): "On the Interaction between the Quantity and Quality of Children," *Journal of Political Economy*, 81(2, Part 2), S279–S288.

Bertrand, M., and J. Pan (2013): "The Trouble with Boys: Social Influences and the Gender Gap in Disruptive Behavior.," *American Economic Journal: Applied Economics*, 5(1), 32–64.

Blau, F. D., and A. J. Grossbergm (1992): "Maternal labour supply and children's cognitive development," *Review of Economics and Statistics*, pp. 474–481.

Bramoullé, Y., H. Djebbari, and B. Fortin (2009): "Identification of peer effects through social networks," *Journal of Econometrics*, 150(1), 41–55.

Bullock, J. G., D. P. Green, and S. E. Ha (2010): "Yes, but what's the mechanism?(don't expect an easy answer).," *Journal of personality and social psychology*, 98(4), 550.

Caeyers, B., and M. Fafchamps (2016): "Exclusion Bias in the Estimation of Peer Effects," *NBER working paper*, (22565).

Carneiro, P., I. L. Garcia, K. Salvanes, and E. Tominey (2015): "Intergenerational Mobility and the Timing of Parental Income," *IZA working paper*, (9479).

Carneiro, P., K. V. Løken, and K. G. Salvanes (2015): "A Flying Start? Maternity Leave Benefits and Long-Run Outcomes of Children," *Journal of Political Economy*, 123(2), 365–412.

Cornelissen, T., C. Dustmann, A. Raute, and U. Schönberg (2018): "Who Benefits from Universal Child Care? Estimating Marginal Returns to Early Child Care Attendance," *Journal of Political Economy*, 126(6), 2356–2409.

Cornelissen, T., C. Dustmann, and U. Schönberg (2017): "Peer Effects in the Workplace," *American Economic Review*, 107(2), 425–56.

Cunha, F., and J. Heckman (2007): "The Technology of Skill Formation Author(s): Source: T," *American Economic Review*, 97(c), 31–47.

Dahl, B. G. B., and L. Lochner (2012): "The Impact of Family Income on Child Achievement : Evidence from the Earned Income Tax Credit," *The American Economic Review*, 102(5), 1927–1956.

Danzer, N., and V. Lavy (2013): "Parental leave and children's schooling outcomes: Quasi-experimental evidence from a large parental leave reform," Discussion paper, national bureau of economic research.

De Giorgi, G., A. Frederiksen, and L. Pistaferri (2015): "Consumption network effects," *Working Paper*, (November).

De Giorgi, G., M. Pellizzari, and S. Radaelli (2015): "Identifification of Social Interactions through Partially Overlapping Peer Groups," *American Economic Journal: Applied Economics*, 2(April).

Dotti Sani, G. M., and J. Treas (2016): "Educational gradients in parents' child-care time across countries, 1965–2012," *Journal of Marriage and Family*, 78(4), 1083–1096.

Dustmann, C., and U. Schönberg (2012): "Expansions in maternity leave coverage and children's long-term outcomes," *American Economic Journal: Applied Economics*, 4(3), 190–224.

Ermisch, J., and M. Francesconi (2013): "The effect of parental employment on child schooling," *Journal of Applied Econometrics*, 28, 796–822.

Fagereng, A., M. Mogstad, and M. Ronning (2018): "Why do wealthy parents have wealthy children?," *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2019-22).

Fan, X., H. Fang, and S. Markussen (2015): "Mothers' Employment and Children's Educational Gender Gap," Discussion paper, National Bureau of Economic Research.

Firpo, S., N. M. Fortin, and T. Lemieux (2009): "Unconditional quantile regressions," *Econometrica*, 77(3), 953–973.

Guryan, J., E. Hurst, and M. Kearney (2008): "Parental Education and Parental Time with Children," *Journal of Economic Perspectives*, 22(3), 23–46.

Heckman, B. J., R. Pinto, and P. Savelyev (2013): "Understanding the Mechanisms Through Which an Influential Early Childhood Program Boosted Adult Outcomes †," 103(6), 2052–2086.

Heckman, J. J., and S. Mosso (2014): "The economics of human development and social mobility," *Annu. Rev. Econ.*, 6(1), 689–733.

Heckman, J. J., and R. Pinto (2015): "Econometric mediation analyses: Identifying the sources of treatment effects from experimentally estimated production technologies with unmeasured and mismeasured inputs," *Econometric reviews*, 34(1-2), 6–31.

Hill, C. R., and F. P. Stafford (1974): "Allocation of Time to Preschool Children and Educational Opportunity.," *Journal of Human Resources*, 9(3).

Hinke, S. v., G. Leckie, and C. Nicoletti (2019): "The Use of Instrumental Variables in Peer Effects Models," *Oxford Bulletin of Economics and Statistics*.

Huebener, M., D. Kuehnle, and C. K. Spiess (2019): "Parental leave policies and socio-economic gaps in child development: Evidence from a substantial benefit reform using administrative data," *Labour Economics*, 61, 101754.

Imai, K., L. Keele, D. Tingley, and T. Yamamoto (2011): "Unpacking the black box of causality: Learning about causal mechanisms from experimental and observational studies," *American Political Science Review*, 105(4), 765–789.

KALIL, A. (2015): "Inequality begins at home: The role of parenting in the diverging destinies of rich and poor children," in *Families in an era of increasing inequality*, pp. 63–82. Springer.

KALIL, A., R. RYAN, AND M. COREY (2012): "Diverging destinies: Maternal education and the developmental gradient in time with children," *Demography*, 49(4), 1361–1383.

LEE, L.-F., X. LIU, AND X. LIN (2010): "Specification and estimation of social interaction models with network structures," *The Econometrics Journal*, 13(2), 145–176.

LEWBEL, A., S. NORRIS, K. PENDAKUR, AND X. QU (2018): "Consumption Peer Effects and Utility Needs in India," *Boston College working paper*.

LIU, Q., AND O. N. SKANS (2010): "The duration of paid parental leave and children's scholastic performance," *The BE Journal of Economic Analysis & Policy*, 10(1).

MACHIN, S., AND K. G. SALVANES (2016): "Valuing school quality via a school choice reform," *The Scandinavian Journal of Economics*, 118(1), 3–24.

MACMILLAN, L., AND E. TOMINEY (2019): "Parental Inputs and Socio-Economic Gaps in Early Child Development," .

MAURIN, E., AND J. MOSCHION (2004): "The Social Multiplier and Labour Market Participation of Mothers," *American Economic Journal: Applied Economics*, 1(1), 251–272.

MCLANAHAN, S. (2004): "Diverging destinies: How children are faring under the second demographic transition," *Demography*, 41(4), 607–627.

MOTA, N., M. F. P. E., AND S. ROSENTHAL (2016): "Neighbourhood Effects, Peer Classification, and the Decision of Women to Work," *IZA Discussion Paper*, 9985.

NICOLETTI, C., AND B. RABE (2019): "Sibling spillover effects in school achievement," *Journal of Applied Econometrics*, 34(4), 482–501.

NICOLETTI, C., K. G. SALVANES, AND E. TOMINEY (2018): "The Family Peer Effect on Mothers' Labor Supply," *American Economic Journal: Applied Economics*, 10(3), 206–234.

Olivetti, C., P. E. Z. Y. (2016): "Mothers, peers and gender identity.," *Journal of Applied Econometrics*, 904.

Pearl, J. (2012): "The causal mediation formula—a guide to the assessment of pathways and mechanisms," *Prevention science*, 13(4), 426–436.

Rasmussen, A. W. (2010): "Increasing the length of parents' birth-related leave: The effect on children's long-term educational outcomes," *Labour Economics*, 17(1), 91–100.

Robins, J. M. (2003): "Semantics of causal DAG models and the identification of direct and indirect effects," *Oxford Statistical Science Series*, pp. 70–82.

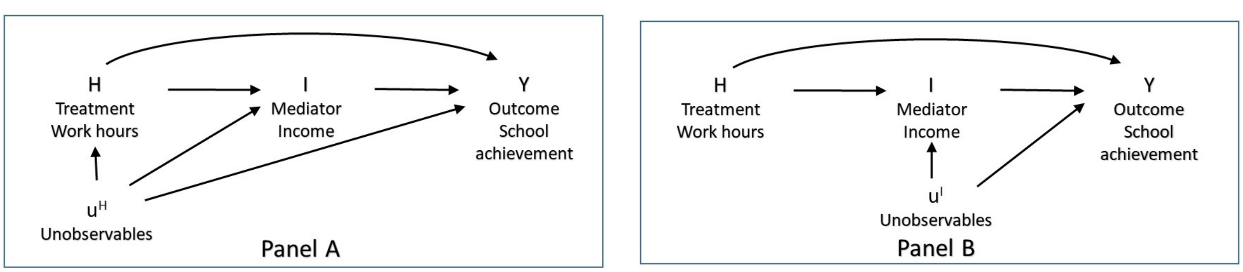
Rosenbaum, P. R. (1984): "The consequences of adjustment for a concomitant variable that has been affected by the treatment," *Journal of the Royal Statistical Society: Series A (General)*, 147(5), 656–666.

VanderWeele, T. (2016): "A unification of mediation and interaction: A 4-way decomposition (Vol 25, pg 749, 2014)," *Epidemiology*, 27(5), E36–E36.

VanderWeele, T. J. (2013): "A three-way decomposition of a total effect into direct, indirect, and interactive effects," *Epidemiology (Cambridge, Mass.)*, 24(2), 224.

Figures

Figure 1: Conceptual diagrams of the mediation pathways



Notes: In each of the two panels the curved arrow represents the direct pathway from H to Y, and the two horizontal arrows represent the mediated pathway from H to Y through I. Panels A shows the confounding effect of the unobservables u^H that causes endogeneity of the treatment, H, in the equation for Y and for I. Panel B shows the confounding effect of u^I that causes endogeneity of the mediator I in the equation for Y.

Figure 2: Graphic representation of confounding effects in the income equation

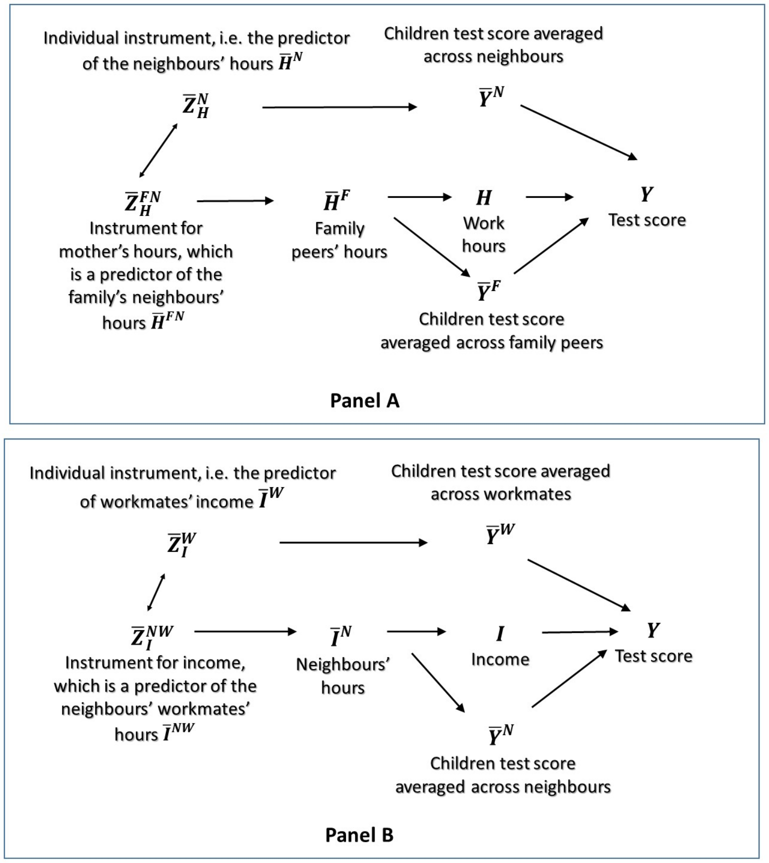
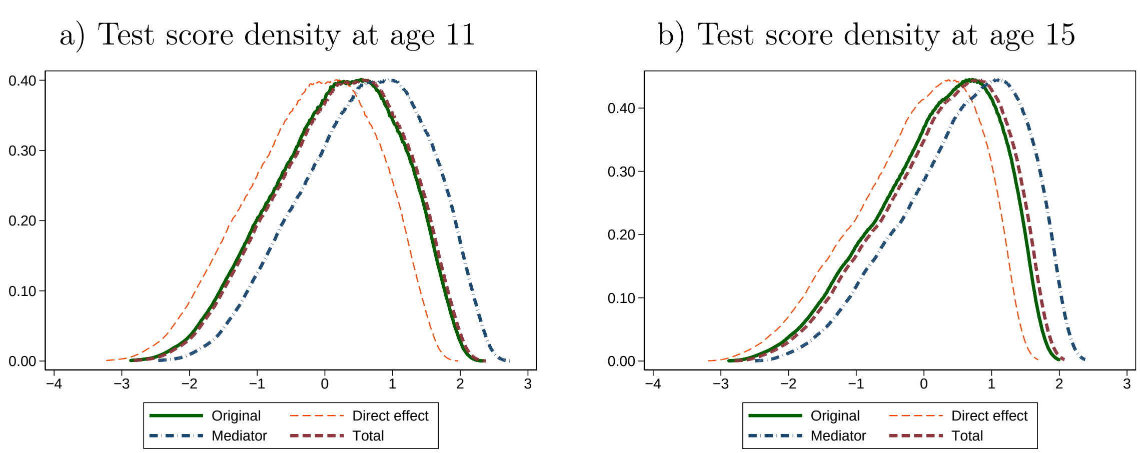


Figure 3: Decomposition analysis: Full sample (benchmark) results



Notes: While "Original" denotes the density of the test score with no changes; the "Direct effect", "Mediator" and "Total" depict the densities shifted by the direct, mediator and total effect, respectively, of an increase in the mother's hours by 10.

Tables

Table 1: Descriptive statistics: Full sample of first births

Variable	Mean	SD
Test score age 11	46.884	14.809
Test score age 15	65.840	19.119
Endogenous variables		
Household income	3.517	1.562
Mothers' hours	19.963	13.297
Instrumental variables		
Father earnings: neighbour's workmates	2.413	0.415
Hours: family's neighbour peers	11.665	12.318
Covariates		
Mothers' education	13.366	2.389
Mothers' degree	0.492	0.500
Mothers' age birth	26.544	4.607
Working before birth	0.765	0.424
Mother participation 1-5	0.885	0.319
Father earnings before birth	1.955	2.050
Father participation year before birth	0.966	0.182
Fathers' education	12.876	2.464
Child month of birth	6.408	3.385
Child year of birth	1998.972	1.411
Child birth weight	3515.809	563.496
Individual Ivs		
Mean neighbourhood test score 11	43.367	6.950
Mean family test score 11	0.013	0.367
Mean neighbourhood test score 15	60.348	9.787
Mean family test score 15	0.026	0.446
Mother hours of neighbours	18.732	5.497
Fathers earnings of workmates	2.658	1.135
Peer group sizes		
Neighbours	62.985	72.275
Coworkers	16.438	35.070
Family	2.396	1.206
Observations	63,022	

Notes: Data source, Norwegian administrative data, first-born children born in 1997-2001.

Table 2: Estimation results, full sample (benchmark) and by child gender

	(1)	(2)	(3)	(4)	(5)	(6)
	Test score at					
	age 11	age 15	age 11	age 11	age 15	age 15
	Full sample	Full sample	Girls	Boys	Girls	Boys
Mothers' hours (γ_H^Y)	-0.036***	-0.030***	-0.015	-0.054***	-0.023	-0.038**
	(0.012)	(0.011)	(0.017)	(0.017)	(0.017)	(0.015)
Household income (γ_I^Y)	0.263***	0.250***	0.154***	0.373***	0.150***	0.346***
	(0.035)	(0.033)	(0.053)	(0.051)	(0.050)	(0.048)
	Income equation					
Mothers' hours (γ_H^I)	0.155***	0.155***	0.152***	0.151***	0.152***	0.151***
	(0.026)	(0.026)	(0.043)	(0.031)	(0.043)	(0.031)
Observations	63,022	63,022	63,022	63,022	63,022	63,022
First stage statistics						
F-statistic IV hours	39.300	39.300	13.480	26.500	13.480	26.500
F-statistic IV income	312.100	312.100	106.570	187.290	106.570	187.290
Exogeneity of H and I in the Y-equation, p-value	0.000	0.000	0.123	0.000	0.123	0.000
Exogeneity of H in the I-equation, p-value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Results from the estimation of the joint model (1). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variables are school test scores at age 11 (col.1, 3, 4) and 15 (col. 2, 5, 6) measured in standard deviations. Income is the yearly household net income in NOK100,000 at 2000 prices and hours is the mother's weekly work hours, both averaged 1-5 years after the first child birth and de-meaned. All remaining controls are measured at or before the child birth (see Table 1). Data sources: Norwegian administrative data, first-born children born in 1997-2001.

Table 3: Decomposition of the total effect of an increase in hours by 10, full sample (benchmark) and by child gender

	(1)	(2)	(3)	(4)	(5)	(6)
	Test score at					
	age 11	age 15	age 11	age 11	age 15	age 15
	Full sample	Full sample	Girls	Boys	Girls	Boys
Direct	-0.362***	-0.305***	-0.151	-0.537***	-0.234	-0.377**
	(0.119)	(0.111)	(0.172)	(0.167)	(0.167)	(0.151)
Mediator	0.407***	0.387***	0.234**	0.565***	0.227**	0.524***
	(0.081)	(0.077)	(0.099)	(0.127)	(0.093)	(0.121)
Total	0.046	0.083	0.083	0.028	-0.007	0.147
	(0.112)	(0.107)	(0.185)	(0.141)	(0.175)	(0.137)
Observations	63,022	63,022	31,042	31,980	31,042	31,980

Notes: The computation of the direct and mediator effects is based on formulas (5) and (6) with coefficients replaced with their estimates of model (1). Standard errors calculated by delta method in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: Norwegian administrative data, first-born children born in 1997-2001.

Table 4: Estimation results by mothers' degree

	(1)	(2)	(3)	(4)
	Test score at			
	age 11	age 11	age 15	age 15
	No degree	Degree	No degree	Degree
Mothers' hours (γ_H^Y)	-0.034**	-0.024	-0.022	-0.027
	(0.016)	(0.024)	(0.015)	(0.022)
Household income (γ_I^Y)	0.193***	0.263***	0.159**	0.257***
	(0.069)	(0.046)	(0.066)	(0.042)
	Income equation			
Mothers' hours (γ_H^I)	0.102***	0.216***	0.102***	0.216***
	(0.022)	(0.064)	(0.022)	(0.064)
Observations	32,009	31,013	32,009	31,013
First stage equation statistics				
F-statistic IV hours	27.260	11.410	27.260	11.410
F-statistic IV income	154.000	210.030	154.000	210.030
Exogeneity of H and I in the Y-equation, p-value	0.037	0.000	0.037	0.000
Exogeneity of H in the I-equation, p-value	0.000	0.000	0.000	0.000

Notes: Results from the estimation of the joint model (1). Variables and controls defined in Table 2. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: Norwegian administrative data, first-born children born in 1997-2001.

Table 5: Decomposition of the total effect of an increase in hours by 10, by mothers' education

	(1)	(2)	(3)	(4)
	Test scores at			
	age 11	age 11	age 15	age 15
	No degree	Degree	No degree	Degree
Direct	-0.341**	-0.237	-0.216	-0.270
	(0.163)	(0.235)	(0.152)	(0.222)
Mediator	0.196**	0.568***	0.162**	0.555***
	(0.081)	(0.192)	(0.076)	(0.186)
Total	-0.144	0.331	-0.054	0.286
	(0.141)	(0.221)	(0.135)	(0.203)
Observations	32,009	31,013	32,009	31,013

Notes: The computation of the direct and mediator effects is based on formulas (5) and (6) with coefficients replaced with their estimates of model (1). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: Norwegian administrative data, first-born children born in 1997-2001.

A Online Appendix

A.1 Allowing for an interaction between income and hours in the test score equation

In Section 5.2 the test score equations at ages 11 and 15 are modelled as in model (1) with the additional interaction between I and H.

$$Y = \gamma_0'^Y + H\gamma_H'^Y + I\gamma_I'^Y + I \cdot H\gamma_{I,H}'^Y + \mathbf{X}\boldsymbol{\beta}'^Y + u'^Y. \tag{9}$$

Notice that in the above and following equations we use the same notation as in (1) but we add a superscript prime for all parameters and error terms.

Adding the interaction term $I \cdot H$ to the test score equation results in changes in the direct and mediator effects and in an additional term to the total effect, which we term the *interaction effect* of mothers' work hours and household income, given by the equation

$$E(Y_{h_1,I_{h_1}} - Y_{h_1,I_{h_0}} - Y_{h_0,I_{h_1}} + Y_{h_0,I_{h_0}}), \tag{10}$$

which differs from zero only if there are both a mediation and an interaction effect, i.e. if both $\gamma_H'^I$ and $\gamma_{I,H}'^Y$ are not zero.

Adding the interaction term to the test score equation will add the term $(h_1 - h_0)E(I_{h_0})\gamma_{I,H}'^Y$ to the direct effect which becomes

$$E(Y_{h_1,I_{h_0}} - Y_{h_0,I_{h_0}}) = (h_1 - h_0)\gamma_H'^Y + (h_1 - h_0)E(I_{h_0})\gamma_{I,H}'^Y, \tag{11}$$

where the average counterfactual income $E(I_{h_0})$, using the right hand side of the equation for I in (1), can be expressed as

$$E(I_{h_0}) = \gamma_0'^I + h_0\gamma_H'^I + E(\mathbf{X})\boldsymbol{\beta}'^I + E(\mathbf{Z}^I)\boldsymbol{\rho}'^I + E(\mathbf{W}^I)\boldsymbol{\eta}'^I. \tag{12}$$

As in our benchmark estimation of the model (1), we use de-meaned explanatory variables and we consider a decomposition of the total effect of increasing the mother's work hours from a value of h_0 equal to the average hours worked. In this case the second right hand side addend in equation (11) cancels out and the direct effect is simply given by the product of the coefficient on hours in the test score equation $\gamma_H'^Y$ and the change in mothers' hours worked $(h_1 - h_0)$ similarly to our benchmark specification.

Adding the interaction term to the test score equation will lead to a change in the mediator effect into

$$E(Y_{h_0,I_{h_1}} - Y_{h_0,I_{h_0}}) = (h_1 - h_0)\gamma_H'^I[\gamma_I'^Y + h_0\gamma_{I,H}'^Y]. \tag{13}$$

which has the additional term $\gamma_{I,H}'^Y$ corresponding to the interaction between I and H that now contributes to the productivity of household income.

Finally, replacing Y and I in the interaction effect (10) with the right hand side of the corresponding equations in (1), we can show that

$$E(Y_{h_1,I_{h_1}} - Y_{h_1,I_{h_0}} - Y_{h_0,I_{h_1}} + Y_{h_0,I_{h_0}}) = (h_1 - h_0)^2\gamma_H'^I\gamma_{I,H}'^Y. \tag{14}$$

We use formulas (11)-(14), to compute the decomposition analysis of the total effect of an increase of 10 hours in mother's hours into the direct, mediator and interaction effects and results are reported in Table A.11.

Figure A.1: Graphic representation of confounding effects in the income equation

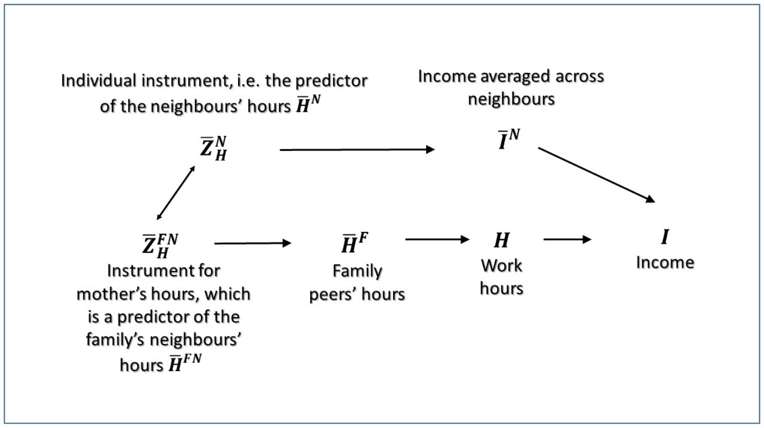
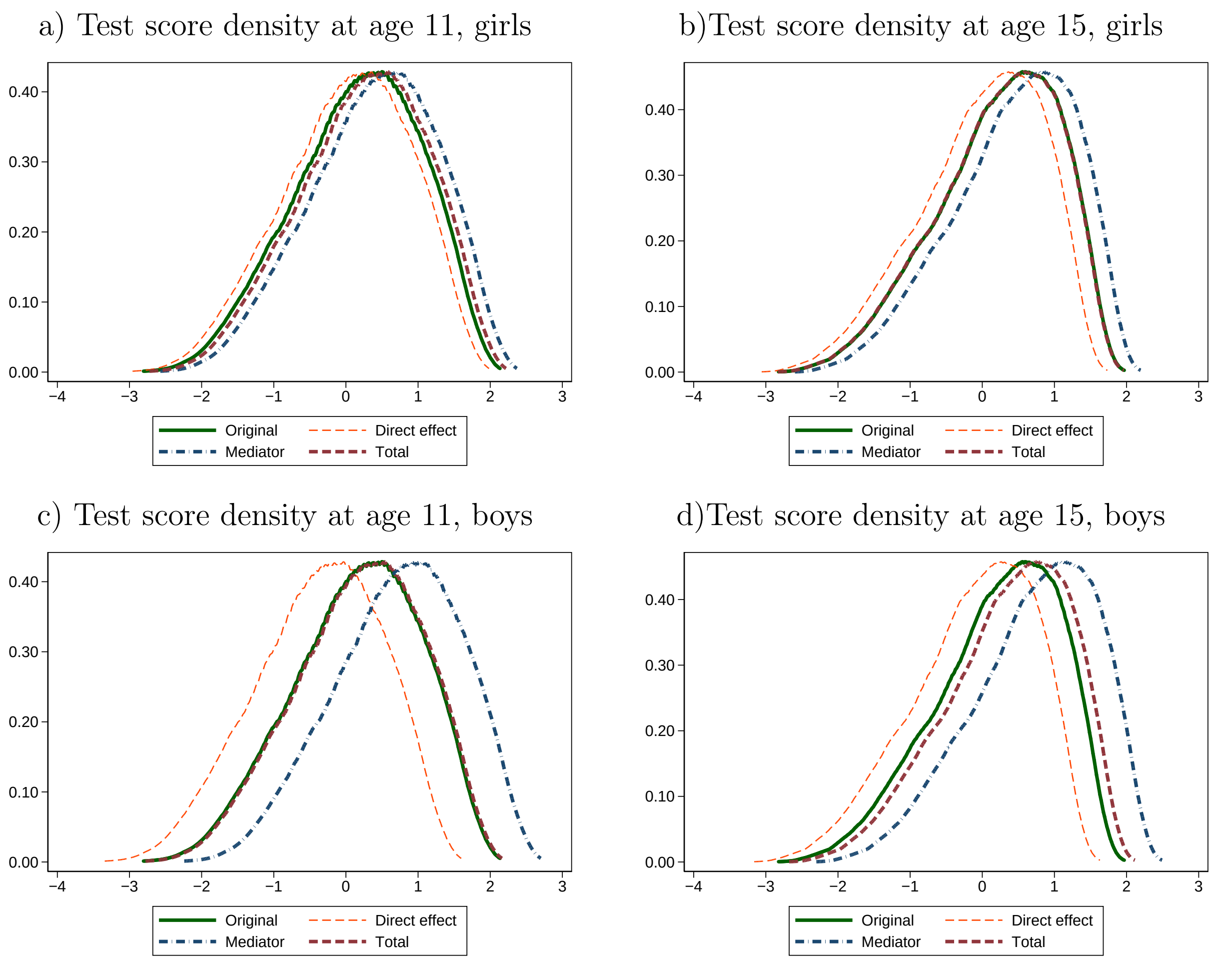
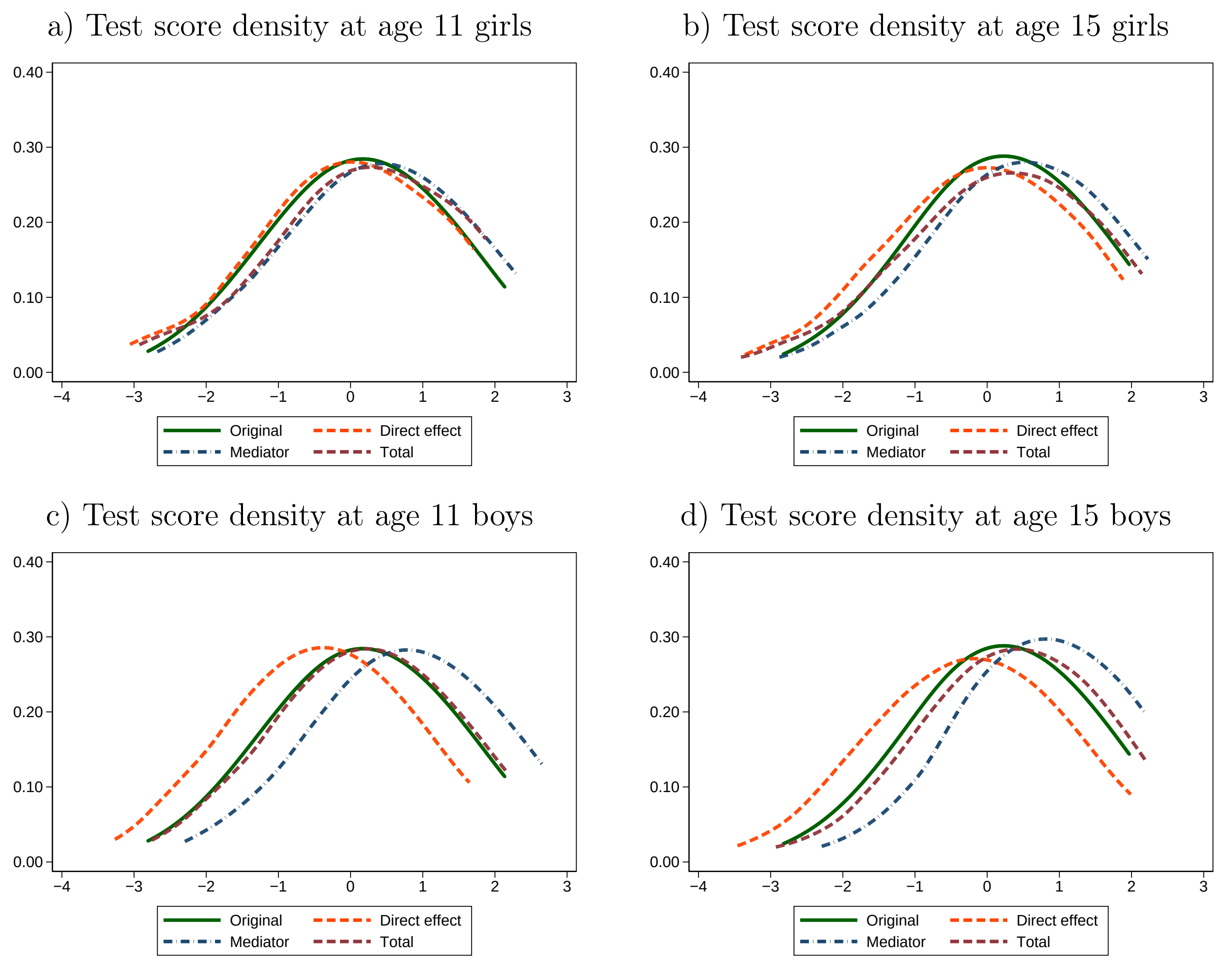


Figure A.2: Decomposition analysis by child gender



Notes: While "Original" denotes the density of the test score with no changes; the "Direct effect", "Mediator" and "Total" depict the densities shifted by the direct, mediator and total effect, respectively, of an increase in the mother's hours by 10.

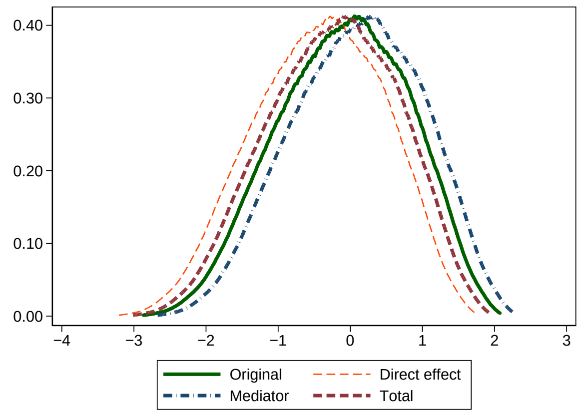
Figure A.3: Decomposition analysis by child gender: Allowing for different effects across the test score distribution



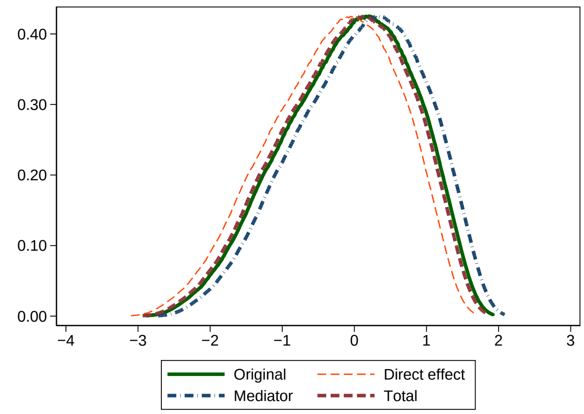
Notes: While "Original" denotes the density of the test score with no changes; the "Direct effect", "Mediator" and "Total" depict the densities shifted by the direct, mediator and total effect, respectively, of an increase in the mother's hours by 10, and allowing the shift to differ across the distribution by using deciles regressions.

Figure A.4: Decomposition analysis by mothers education

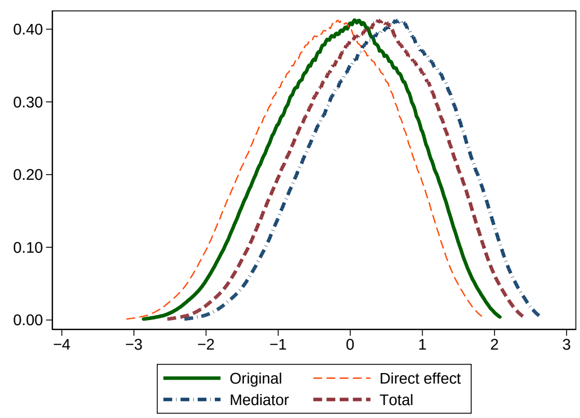
a) Test score density at age 11, no degree



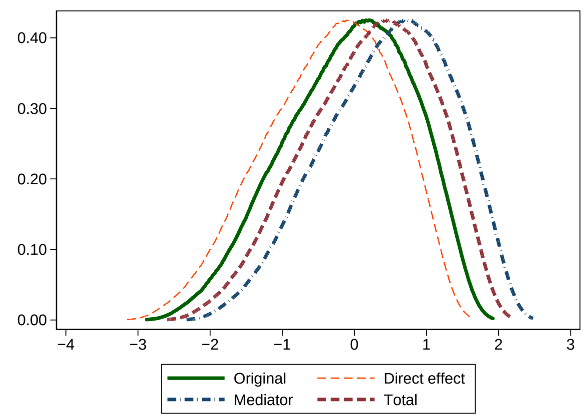
b) Test score density at age 15, no degree



c) Test score density at age 11, degree



d) Test score density at age 15, degree



Notes: While "Original" denotes the density of the test score with no changes; the "Direct effect", "Mediator" and "Total" depict the densities shifted by the direct, mediator and total effect, respectively, of an increase in the mother's hours by 10.

Table A.1: Control and instrumental variables in the three models

Control variables and IVs	Test scores	Earnings	Work hours
Endogenous variables			
Mean household income age 1-5	Yes		
Mean hours worked age 1-5	Yes	Yes	
Mother variables			
Years of schooling	Yes	Yes	Yes
Age at 1st child	Yes	Yes	Yes
Work before 1st child	Yes	Yes	Yes
Father variables			
Income before 1st child	Yes	Yes	Yes
Participation before 1st child	Yes	Yes	Yes
Years of schooling	Yes	Yes	Yes
Child variables			
Month of birth dummies	Yes	Yes	Yes
Year of birth dummies	Yes	Yes	Yes
Birth weight level and squared	Yes	Yes	Yes
Instrumental variables			
Father earnings of neighbour's workmates		Yes	
Hours of family's neighbour peers			Yes
Individual IVs			
Fathers earnings of workmates	Yes	Yes	Yes
Mother hours of neighbours	Yes	Yes	Yes
Mean family test score	Yes	Yes	Yes
Mean neighbourhood test score	Yes	Yes	Yes

Table A.2: Full benchmark regression estimates

Equation	(1) Test score 11	(2) Test score 15	(3) Income	(4) Hours
Mothers' hours	-0.036***	-0.030***	0.155***	
	(0.012)	(0.011)	(0.026)	
Household income	0.263***	0.250***		
	(0.035)	(0.033)		
Instrumental variables				
Father earnings of neighbour's workmates			0.285***	
			(0.016)	
Hours 1 year after birth of family's neighbour peers				0.025***
				(0.004)
Covariates				
Male	-0.005	-0.065***	0.021	-0.050
	(0.007)	(0.007)	(0.015)	(0.096)
Child birth weight	0.043***	0.035***	0.009	0.051
	(0.004)	(0.004)	(0.008)	(0.048)
Child birth weight squared	-0.007***	-0.004**	0.006	-0.029
	(0.002)	(0.002)	(0.004)	(0.026)
Mother years schooling	0.080***	0.080***	-0.066***	0.628***
	(0.008)	(0.007)	(0.017)	(0.025)
Mother work before 1st child	0.250**	0.229**	-0.847***	8.245***
	(0.098)	(0.092)	(0.213)	(0.119)
Mother age 1st child	0.009	0.013**	0.001	0.471***
	(0.006)	(0.006)	(0.012)	(0.011)
Father income before 1st child	-0.038***	-0.034***	0.177***	-0.012
	(0.007)	(0.006)	(0.004)	(0.024)
Father participation before 1st child	-0.047	-0.014	0.182*	3.310***
	(0.049)	(0.045)	(0.096)	(0.268)
Father years schooling	0.036***	0.042***	0.091***	0.099***
	(0.004)	(0.004)	(0.004)	(0.023)
Individual Ivs				
Father earnings of workmates	-0.041***	-0.035***	0.228***	0.171***
	(0.010)	(0.009)	(0.009)	(0.044)
Mother hours 1 year after birth of neighbours	0.005***	0.004**	-0.012***	0.131***
	(0.002)	(0.002)	(0.004)	(0.009)
Mean child test scores of family peers	0.069***	0.064***	-0.005	0.245*
	(0.011)	(0.010)	(0.022)	(0.131)
Mean child test scores of neighbour peers	0.008***	0.004***	-0.004	0.098***
	(0.001)	(0.001)	(0.003)	(0.007)
Constant	-0.791**	-0.873**	-1.991***	-27.934***
	(0.369)	(0.345)	(0.708)	(0.569)
Observations	63,022	63,022	63,022	63,022

Notes: The regressions control additionally for child year and month of birth dummies.

Table A.3: Equations for child test scores at age 11 and 15 estimated by OLS

	Test score equation at age 11	age 15
Mothers' hours (γ_H^Y)	0.001***	0.001***
	(0.000)	(0.000)
Household income (γ_I^Y)	0.044***	0.051***
	(0.003)	(0.003)
Observations	63,022	63,022

Notes: Equations for test scores at age 11 (col. 1) and 15 (col 2) estimated separately using OLS. Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01. The school test scores at age 11 and 15 are measured in standard deviations, income is the yearly income in NOK100,000 at 2000 constant prices and hours is the mother's weekly work hours. Both income and hours are averaged between 1 and 5 years after the first child birth and are de-meaned. All remaining controls are measured at or before the child birth (see Table 1) but exclude the instruments. Data sources: Norwegian administrative data, first-born children born in 1997-2001.

Table A.4: Effect of mothers' hours on neighbourhood school quality

	(1)	(2)	(3)	(4)
	Neighbourhood school quality at age			
	age 11	age 11	age 15	age 15
a) Regression estimates	No degree	Degree	No degree	Degree
Mothers' hours (γ_H^Y)	0.138***	0.199***	0.145***	0.180***
	(0.028)	(0.060)	(0.029)	(0.058)
Household income (γ_I^Y)	0.294***	0.201***	0.239***	0.259***
	(0.078)	(0.067)	(0.074)	(0.072)
b) Decomposition				
Direct	1.376***	1.994***	1.446***	1.803***
	(0.280)	(0.598)	(0.289)	(0.578)
Mediator	0.307***	0.387***	0.248***	0.478***
	(0.104)	(0.137)	(0.094)	(0.139)
Total	1.683***	2.381***	1.694***	2.281***
	(0.313)	(0.616)	(0.316)	(0.590)
Observations	32,009	31,013	32,009	31,013

Table A.5: Estimation results: Sample of households with up to 3 children and no marital break up to age 11

	(1)	(2)	(3)	(4)
	Test scores at			
	age 11	age 11	age 15	age 15
a) Regression estimates	No degree	Degree	No degree	Degree
Mothers' hours (γ_H^Y)	-0.032*	-0.029	-0.002	-0.035
	(0.017)	(0.022)	(0.016)	(0.022)
Household income (γ_I^Y)	0.202**	0.272***	0.160**	0.284***
	(0.083)	(0.046)	(0.080)	(0.044)
b) Decomposition				
Direct	-0.324*	-0.292	-0.021	-0.352
	(0.172)	(0.225)	(0.159)	(0.220)
Mediator	0.194**	0.627***	0.153*	0.655***
	(0.089)	(0.206)	(0.084)	(0.209)
Total	-0.130	0.335	0.132	0.302
	(0.158)	(0.248)	(0.153)	(0.236)
Observations	29,253	28,152	29,253	28,152

Notes: Equations for test scores at age 11 (col. 1) and 15 (col 2) estimation of the joint model (1). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The school test scores at age 11 and 15 are measured in standard deviations, income is the yearly income in NOK100,000 at 2000 constant prices and hours is the mother's weekly work hours. Both income and hours are averaged between 1 and 5 years after the first child birth and are de-meaned. All remaining controls are measured at or before the child birth (see Table 1). Data sources: Norwegian administrative data, first-born children born in 1997-2001.

Table A.6: Sensitivity: Control for household income and mothers' hours age 6-11

	(1)	(2)	(3)	(4)
	Test scores at			
	age 11	age 15	age 11	age 15
	Controlling for income at 6-11		Controlling for hours at 6-11	
a) Regression estimates				
Mothers' hours	-0.050***	-0.042***	-0.045***	-0.038**
	(0.011)	(0.010)	(0.017)	(0.016)
Household income	0.403***	0.374***	0.267***	0.254***
	(0.065)	(0.061)	(0.038)	(0.036)
b) Decomposition				
Direct	-0.497***	-0.423***	-0.445***	-0.378**
	(0.111)	(0.104)	(0.172)	(0.160)
Mediator	0.519***	0.481***	0.492***	0.468***
	(0.106)	(0.100)	(0.111)	(0.106)
Total	0.022	0.058	0.047	0.090
	(0.125)	(0.119)	(0.138)	(0.131)
Observations	63,020	63,020	63,020	63,020

Notes: Equations for test scores at age 11 (col. 1) and 15 (col 2) estimation of the joint model (1). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The school test scores at age 11 and 15 are measured in standard deviations, income is the yearly income in NOK100,000 at 2000 constant prices and hours is the mother's weekly work hours. Both income and hours are averaged between 1 and 5 years after the first child birth and are de-meaned. All remaining controls are measured at or before the child birth (see Table 1) and additionally mean household income between ages 6-11. Data sources: Norwegian administrative data, first-born children born in 1997-2001.

Table A.7: Sensitivity: Nonlinearity in income and hours in the test score equations, quadratic specification

a) Regression estimates	(1) Test score at age 11	(2) age 15
Mothers' hours	-0.036***	-0.032***
	(0.012)	(0.012)
Household income	0.264***	0.263***
	(0.037)	(0.035)
Hours squared	0.000	-0.000
	(0.000)	(0.000)
Income squared	0.000	-0.003***
	(0.001)	(0.001)
b) Decomposition		
Direct	-0.364***	-0.324***
	(0.125)	(0.119)
Mediator	0.409***	0.408***
	(0.070)	(0.067)
Total	0.045	0.084
	(0.119)	(0.113)
Observations	63,022	63,022

Notes: Equations for test scores at age 11 (col. 1) and 15 (col 2) estimation of the joint model (1) using a control function approach. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The school test scores at age 11 and 15 are measured in standard deviations, income is the yearly income in NOK100,000 at 2000 constant prices and hours is the mother's weekly work hours. Both income and hours are averaged between 1 and 5 years after the first child birth and are de-meaned. All remaining controls are measured at or before the child birth (see Table 1). Data sources: Norwegian administrative data, first-born children born in 1997-2001.

Table A.8: Sensitivity: Nonlinearity in hours in the test score equations, splines in hours

a) Regression results	(1)	(2)
	Test score at	
	age 11	age 15
Mothers' hours: Q1	-0.039***	-0.033***
	(0.013)	(0.012)
Mothers' hours: Q2	0.005*	0.003
	(0.003)	(0.002)
Mothers' hours: Q3	-0.004**	-0.002
	(0.002)	(0.002)
Mothers' hours: Q4	0.005*	-0.003
	(0.002)	(0.002)
Household income	0.266***	0.253***
	(0.036)	(0.035)
b) Decomposition		
Direct: Q1	-0.393***	-0.325***
	(0.126)	(0.120)
Direct: Q2	-0.346***	-0.294**
	(0.125)	(0.119)
Direct: Q3	-0.388***	-0.311***
	(0.125)	(0.119)
Direct: Q4	-0.341***	-0.338***
	(0.126)	(0.119)
Mediator	0.413***	0.392***
	(0.070)	(0.066)
Total: Q1	0.020	0.067
	(0.120)	(0.114)
Total: Q2	0.067	0.099
	(0.119)	(0.113)
Total: Q3	0.025	0.081
	(0.119)	(0.113)
Total: Q4	0.072	0.054
	(0.120)	(0.114)
Observations	63,022	63,022

Notes: Equations for test scores at age 11 (col. 1) and 15 (col 2) estimation of the joint model (1) using a control function approach. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The school test scores at age 11 and 15 are measured in standard deviations, income is the yearly income in NOK100,000 at 2000 constant prices and hours is the mother's weekly work hours. Both income and hours are averaged between 1 and 5 years after the first child birth and are de-meaned. All remaining controls are measured at or before the child birth (see Table 1). Data sources: Norwegian administrative data, first-born children born in 1997-2001.

Table A.9: Sensitivity: Nonlinearity in income in the test score equations, splines in income

	(1)	(2)
	Test score at	
	Age 11	Age 15
Mothers' hours	-0.036***	-0.032***
	(0.012)	(0.012)
Income Q1	0.214***	0.198***
	(0.043)	(0.041)
Income Q2	-0.046	0.026
	(0.055)	(0.052)
Income Q3	0.153*	0.048
	(0.087)	(0.083)
Income Q4	-0.052	0.014
	(0.111)	(0.105)
Income Q5	0.025	0.014
	(0.121)	(0.115)
Income Q6	0.024	0.032
	(0.119)	(0.113)
Income Q7	-0.050	-0.023
	(0.105)	(0.099)
Income Q8	-0.014	-0.097
	(0.080)	(0.076)
Income Q9	0.002	0.012
	(0.052)	(0.050)
Income Q10	-0.007	0.008
	(0.029)	(0.027)
Observations	63,022	63,022

Notes: Equations for test scores at age 11 (col. 1) and 15 (col 2) estimation of the joint model (1) using a control function approach. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The school test scores at age 11 and 15 are measured in standard deviations, income is the yearly income in NOK100,000 at 2000 constant prices and hours is the mother's weekly work hours. Both income and hours are averaged between 1 and 5 years after the first child birth and are de-meaned. All remaining controls are measured at or before the child birth (see Table 1). Data sources: Norwegian administrative data, first-born children born in 1997-2001.

Table A.10: Sensitivity: Decomposition, splines in income

	(1) Test score at Age 11	(2) Age 15
Direct	-0.359***	-0.320***
	(0.125)	(0.119)
Mediator: Q1	0.332***	0.307***
	(0.074)	(0.070)
Mediator: Q2	0.261***	0.347***
	(0.088)	(0.087)
Mediator: Q3	0.498***	0.422***
	(0.116)	(0.108)
Mediator: Q4	0.418***	0.444***
	(0.124)	(0.120)
Mediator: Q5	0.456***	0.465***
	(0.128)	(0.122)
Mediator: Q6	0.494***	0.514***
	(0.124)	(0.119)
Mediator: Q7	0.415***	0.479***
	(0.107)	(0.105)
Mediator: Q8	0.393***	0.329***
	(0.089)	(0.083)
Mediator: Q9	0.397***	0.348***
	(0.076)	(0.071)
Mediator: Q10	0.386***	0.360***
	(0.070)	(0.067)
Total: Q1	-0.027	-0.013
	(0.121)	(0.114)
Total: Q2	-0.098	0.027
	(0.130)	(0.126)
Total: Q3	0.139	0.102
	(0.150)	(0.141)
Total: Q4	0.059	0.123
	(0.157)	(0.150)
Total: Q5	0.097	0.145
	(0.160)	(0.153)
Total: Q6	0.135	0.194
	(0.157)	(0.150)
Total: Q7	0.056	0.159
	(0.144)	(0.139)
Total: Q8	0.034	0.009
	(0.131)	(0.123)
Total: Q9	0.038	0.028
	(0.123)	(0.116)
Total: Q10	0.027	0.040
	(0.119)	(0.113)
Observations	63,022	63,022

Table A.11: Sensitivity: Allowing for interaction between hours and income in the test score equation

	(1)	(2)
	Test score at	
	age 11	age 15
Mothers' hours	-0.036***	-0.032***
	(0.012)	(0.012)
Household income	0.264***	0.256***
	(0.037)	(0.035)
Hours · Income	0.000	-0.000**
	(0.000)	(0.000)
b) Decomposition		
Direct	-0.363***	-0.315***
	(0.125)	(0.119)
Mediator	0.409***	0.397***
	(0.070)	(0.067)
Interaction	0.000	-0.000**
	(0.000)	(0.000)
Total	0.046	0.082
	(0.119)	(0.113)
Observations	63,022	63,022

Notes: Equations for test scores at age 11 (col. 1) and 15 (col 2) estimation of the joint model (1) using a control function approach. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The school test scores at age 11 and 15 are measured in standard deviations, income is the yearly income in NOK100,000 at 2000 constant prices and hours is the mother's weekly work hours. Both income and hours are averaged between 1 and 5 years after the first child birth and are de-meaned. All remaining controls are measured at or before the child birth (see Table 1). Data sources: Norwegian administrative data, first-born children born in 1997-2001.

Table A.12: Total effect of a 1 hour increase in mothers' working hours estimated using 2SLS

	(1) Test scores at age 11	(2) age 15
Mothers' hours	0.004	0.008
	(0.011)	(0.011)
Observations	63,022	63,022

Notes: Equations for test scores at age 11 (col. 1) and 15 (col 2) estimated using 2SLS. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The school test scores at age 11 and 15 are measured in standard deviations, income is the yearly income in NOK100,000 at 2000 constant prices and hours is the mother's weekly work hours. Both income and hours are averaged between 1 and 5 years after the first child birth and are demeaned. All remaining controls are measured at or before the child birth (see Table 1). Data sources: Norwegian administrative data, first-born children born in 1997-2001.