Does parental employment affect children's educational attainment?

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Abstract

This paper analyzes whether there exists a causal relationship between parental employment and children's educational attainment. We address potential endogeneity problems due to (i) selection of parents in the labor market by estimating a model on sibling differences and (ii) reverse causality by focusing on parents' employment when children are aged 0-3. We use data from the German Socioeconomic Panel that provide information on household income, parental employment, and time spent with child care. Our approach disentangles income and time effects of parental employment. Overall, we find little support that parental employment affects children's educational attainment. Controlling for household income, we can rule out that having a mother who works one hour more per week lowers the probability of high secondary track attendance by more than 0.1%.

JEL classification: C20, D13, I21, J13, J22

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1 Introduction

Over the last decades, female labor market participation rates and especially those of mothers with young children have increased tremendously in many countries. In the US, 47% of mothers with children below age 6 worked in 1975. By 2006, this share had increased to 71% (Chao & Rones, 2007, Table 7). In Germany, 35% of mothers with children below age 6 worked in 1974, but 52% in 2004. In contrast, labor market participation rates of German fathers have remained very stable at about 88%.[1]

Precise knowledge about how parental employment affects children's long-term outcomes such as educational attainments or labor market success is crucial for the evaluation of many policy programs. For example, US welfare reforms in the 1990s pushed welfare recipients and in particular welfare dependent single mothers to find employment (compare Blank, 2002). Reforms were motivated by the belief that parental work is the best way out of poverty for parents and children. If, however, having working parents hurts the educational and labor market prospects of children such reforms may be counterproductive in the long run. To give another example, the German government's decision to substantially expand and subsidize day care facilities for children below age 3 has lead to emotional and controversial debates in the German public. Opponents of day care expansion consider full-time parental child care to be decisive for children's cognitive and emotional development. Proponents argue that parent-child interactions can be substituted by high quality non-parental child care and that increases in family income may also benefit children.

This paper is the first to use a large German household panel data set, the German Socioeconomic Panel (GSOEP), to analyze whether parental employment hurts or benefits children's educational attainments. We separately analyze two effects of parental employment: first, the effect on income that may influence child-related investments, i.e. we control for total household income. Second, we use three different measures of parental time inputs in raising their children to capture the "time effect" of parental employment: besides the standard indirect measures that have been used in the related literature (namely, weekly hours worked and the number of years in which parents work full-time, part-time or not at all) the GSOEP data provide a direct, self-reported measure of the hours parents spent on child care on a typical weekday when children are aged 0-3. Our measure of

[1] Figures stem from an inquiry at the Federal Statistical Office of Germany. The 35% in 1974 refer to West Germany only.

educational attainment and dependent variable is attendance or completion of high secondary school track (so called Gymnasium) which is the only track that provides direct access to university.

We explicitly approach potential endogeneity problems. First, to take selection of parents in the labor market into account we estimate a model on sibling differences that controls for all unobserved time-invariant parent and household characteristics. Second, we address the potential reverse causality problem, i.e. the fact that parents' decisions to work may be influenced by their child's ability which in turn affects educational attainment. We focus on parental employment when children are aged 0-3 such that a child's ability is not yet fully revealed, exclude disabled children from the analysis and use parents' years of education as a proxy for their child's ability.

We do not find any evidence that parental employment hurts children's educational attainment. Controlling for household income, we can statistically rule out that having a mother who works one hour more per week lowers the probability of high secondary track attendance by more than 0.1 percentage points. Actually, all coefficients of maternal employment are positive, but not significant at conventional levels (though at a 9 to 11% significance level). Coefficients of fathers' employment and parental time spent on child care are precisely estimated, but too small to be significant. Testing for equality of mother's and father's time input coefficients, we cannot reject that parents' time inputs are substitutes.

Table 1 reviews results from previous economic studies that investigate the relationship between parental employment and children's educational attainment. In sum, evidence is very inconclusive: some studies predict a negative effect of parental employment on children's educational attainment, some a positive one and the remainder insignificant effects or effects that differ by subsamples such as sex or race of the child.[2] Table 1 also reveals some characterizing features of existing studies. First and most importantly, except for Ermisch & Francesconi (2002) they ignore problems that arise due to omitted variables such as a child's ability or selection of parents into the labor market. In contrast, this paper addresses the conditions under which we obtain consistent estimates explicitly and estimates a model on sibling differences to control for unobserved parent and household characteristics. Second, all studies in Table 1 use indirect measures of parental time inputs such as the type of

[2] Taking a slightly different perspective, Magnuson, Ruhm, & Waldfogel (2007) and Loeb, Bridges, Bassok, Fuller, & Rumberger (2007) examine the effects of attending center based childcare below age 5. Both studies find that childcare attendance increases math and reading skills at school entry, but is also associated with higher levels of behavioral problems.

Table 1: Related literature

study	data source, country	outcome	estimation method	effect of parental employment
Ermisch and Francesconi (2002)	British Household Panel Survey, UK	highest educational qualification (A level or more)	logit, linear probability models, sibling differences model	mother works part-time: level estimates: (-) ns sibling difference est.: (-) 10 mother works full-time: level estimates: (-) ns sibling difference est.: (-) 5 father works: level estimates: (+) 5 sibling difference est.: (-) ns
Graham, Beller, and Hernandez (1994)	Current Population Survey, US	years of schooling at ages 16-20	2SLS, first stage: IV for child support	mother worked outside home: (+) 1
Haveman, Wolfe, and Spaulding (1991)	Panel Study of Income Dynamics, US	high school graduation	probit model	years mother worked: (+) 1
Hill and Duncan (1987)	Panel Study of Income Dynamics, US	years of schooling at ages 27-29	OLS, gender specific	mother's work hours: for men: (-) 5 for women: (-) ns
Kiernan (1996)	National Child Development Study, UK	no degree	descriptive statistics, logit model	mother's non-employment: for men: no effect for women: (+) 1
Krein and Beller (1988)	National Longitudinal Surveys, US	years of schooling at age 26	OLS, gender and race specific	mother ever worked outside home at least 6 months at ages 0-18: white men: (-) 1 white women: (-) ns black men: (+) ns black women: (-) ns
O'Brien and Jones (1999)	survey and time-use diaries in 6 schools in East London, UK	highest / lowest national test scores	logit model	low educational outcome: father works full time and mother full time: (-) ns mother part-time: (-) 5 high educational outcome: father works full-time and mother full time: (+) ns mother part-time: (+) 10

comments: (-) indicates a negative sign, (+) a positive sign

ns: not significant; 1, 5, 10: significant at a 1, 5, 10 percent significance level parental employment (full-time, part-time or none) or years worked.[3] An advantage of the GSOEP data set is that it contains very detailed information on the time parents spent on child care. Third, only two studies (Ermisch & Francesconi, 2002 and O'Brien & Jones, 1999) report estimates on the effect of father's employment. Our paper estimates the effects of parental employment separately for mothers and fathers and also the joint effect of e.g. hours worked.

Haveman & Wolfe (1995) review studies on the effects of parental employment on a broad range of children's outcomes such as high school graduation, years of schooling, out-of-wedlock fertility, or adult earnings. All reviewed studies use US data and do not address endogeneity problems. Ermisch & Francesconi (2005) survey the more recent literature on parental employment and children's well-being covering studies that use data from countries different from the US, mainly from UK.

Using German administrative data Dustmann & Schönberg (2009) analyze the effect of three extensions in maternity leave coverage on children's later attendance of high secondary track and wages. They compare cohorts of children born shortly before and after the reforms. Although reforms induced women to delay their return to work, the authors do not find that an expansion in maternity leave legislation improves child outcomes. By exploiting unexpected changes in legislation the authors can nicely infer causal effects at the cohort level. We consider our approach complementary to theirs: using individual level instead of cohort data we can evaluate the importance of numerous individual and family characteristics for child outcomes.

A couple of papers use GSOEP data to explain high secondary track attendance, but none analyzes the overall impact of parental employment. Büchel & Duncan (1998) explore the role of parents' social activities, Francesconi, Jenkins, & Siedler (2010) the impact of growing up in a family headed by a single mother. Tamm (2008) is most closely related to our study because the paper investigates the effect of parental income on high secondary track attendance. Our study aims at estimating the overall effect of parental employment on high secondary track attendance by separately analyzing income and time effect of parental employment. While having parents who work more obviously results in a higher family income for a given family, a straightforward mapping from family income to time spent on child care or hours

[3] Haveman, Wolfe, & Spaulding (1991) use *estimated* parental time spent on child care as explanatory variable. They do not have information on time spent on child care in their original data but construct it from a second data set. Using the second data set they regress child care time on explanatory variables that their original data and the second data set have in common and then apply coefficients to their original data set to construct estimates of child care time.

worked is not possible. In contrast to Tamm (2008), we estimate the effect of the amount of time that parents work or spend on child care.

The structure of the paper is as follows: section 2 offers basic information on the German school system, section 3 provides a brief overview on the GSOEP data set. Economic framework and estimation methods are discussed in section 4. In section 5, we present results from level and sibling difference regressions as well as non-parametric Kernel density estimates. Section 6 concludes.

2 Institutional background: the German school system

In Germany, all students jointly go to elementary school for at least four years. After elementary school, usually at age 10, students proceed to secondary education. The secondary education system is organized in three main tracks: Least academic and most vocational general secondary school track (Hauptschule, grades 5 to 9) provides basic secondary education and prepares for an apprenticeship in a blue collar job. Intermediate secondary school track (Realschule, grades 5 to 10 or 11) is usually followed by an apprenticeship in a white collar job. Only students of the most academic track, the high secondary school track (Gymnasium, grades 5 to 12 or 13), obtain a final degree that provides direct access to university.

Education is regulated by the states (Bundesländer). In all states, track choice after elementary school is influenced by a recommendation of elementary school teachers that is mainly based on performance. The extent to which parents can influence their child's school track differs substantially across states. In some states the tracking decision is delayed from fourth to sixth grade. Furthermore, some states have a comprehensive school type (Gesamtschule) that comprises all three tracks. All states have schools for children with special needs due to physical or mental disabilities (Sonderschule). Finally, there are very few so-called Waldorf schools that are private and follow a special pedagogy. In our data, about 88% of students are part of the standard three track system: 20% attend general, 34% intermediate, and 34% high secondary school track. In all states, secondary education is compulsory up to grade 9 and provided free of charge.

Changing secondary school track after initial choice is possible, but relatively rare. Using GSOEP data on West Germans born between 1970 and 1984, Tamm (2008) compares secondary school tracks attended at age 14 with the highest secondary school degree obtained at age 21. He finds that between 60% and 70% of students obtain the degree of the secondary school track they attended at age 14.

Secondary school track is an important determinant of labor market outcomes later in life. Using GSOEP data, Dustmann (2004) shows that having successfully attended the high (intermediate) instead of the general secondary school track increases the wage at labor market entry by 29.3% for men and 37.7% for women (15.9% for men and 26.7% for women, respectively). This holds true even when controlling for post-secondary education that is strongly influenced by secondary school track. The wage premium increases to far more than 50% for a high instead of general secondary education degree when post-secondary education is not controlled for.

3 Data

We use data from the German Socioeconomic Panel (GSOEP). The GSOEP is a representative panel study of German households that covers the years 1984 until 2006. In addition to household level information, individual information is available. Data cover a wide range of topics such as individual attitudes and health status, job characteristics, unemployment and income, family characteristics and living conditions. For children up to age 15, personal information is provided by the head of the household. We use subsamples A to D, i.e., data on households living in East and West Germany irrespective of their nationality.[4] Haisken-DeNew & Frick (2003) provide a detailed description of the GSOEP.

Our dependent variable is binary and indicates whether a child attends high secondary school track or does not, i.e., attends general or intermediate secondary education.[5] Hence, it focuses on whether children will obtain access to university after finishing school[6] or do an apprenticeship as both general and intermediate

[4]Sampling of East German households started in 1990. For accuracy reasons, East German and foreign households are oversampled in the GSOEP data. To account for oversampling we use the cross-sectional weights provided in the GSOEP data.

[5]Reducing the three track system to a binary variable makes our results easier to interpret and better comparable to those of the related literature, see for example Puhani & Weber (2007), Büchel & Duncan (1998) and Francesconi, Jenkins, & Siedler (2010). Furthermore, estimating an ordered logit model on sibling differences requires the additional assumption that the difference between general and intermediate secondary track is the same as the difference between intermediate and high secondary track.

[6]About 70% of students who finish high secondary track successfully attend university after-

secondary track students usually do. We use the latest available information on track choice to minimize inaccurateness caused by later changing of tracks. Children attending other types of schools are excluded from our analysis.

Parents' time inputs are the primary variables of interest. We use three alternative variables to check the sensitivity of our results: (i) weekly hours worked, (ii) the number of years in which parents have a full-time, part-time or no job, and (iii) hours spent on child care on an average weekday. While hours spent on child care is the most direct measure, it is also the most subjective one. Some parents claim to devote 24 hours per day to child care, others, who also stay at home, state much lower numbers. Type of employment and hours worked do not capture time inputs directly, but are significantly negatively correlated with hours spent on child care for both fathers and mothers (with correlation coefficients of about $\rho = -0.30$). For the largest part of our analysis we use averages of each of these three variables over a child's first three years. There are two reasons for focusing on the first three years. First, this is the period that is most debated in public. Second, as will become clear in the next section, our identifying assumption is that parents do not know their child's ability as long as their child is sufficiently small and, thus, cannot condition their employment decision on their child's ability. This assumption is more plausible the younger a child is.

A list of all explanatory variables, their means and sample sizes is displayed in Table 2.

4 Economic framework, identification, and estimation

Why should parental employment affect children's educational attainments? The very stylized and simplified static framework underlying our empirical analysis assumes that children's educational attainment s_i is a function of parents' time inputs, t_i, and goods and services inputs, x_i, and the child's ability, μ_i: $s_i = f(t_i, x_i, \mu_i)$ where all three first partial derivatives are positive. Both time and good inputs are influenced by parents' employment decisions. On the one hand, we expect parents who work to spend less time with their children (e.g. to play with them or to educate them) which results in a negative "time effect". On the other hand, we expect a positive "input effect". The more parents work the higher is the family income.

wards.

Table 2: Summary statistics

variable	general sample	siblings sample
information on the child		
attends high secondary school track	0.356	0.329
male	0.500	0.507
year of birth	1989.614	1989.835
firstborn child	0.484	0.402
born from January till June	0.508	0.513
information on the household		
total monthly net equivalent income[a],[b]	0.917	0.924
non-German household	0.238	0.238
information on the mother		
age at birth <=21	0.117	0.127
age at birth 22-35	0.829	0.838
age at birth >36	0.053	0.035
years of education	11.486	11.549
weekly hours worked[a]	7.743	5.196
time spent on child care per weekday[a]	8.839	9.454
not working (number of years)	2.189	2.338
part-time job (number of years)	0.477	0.451
full-time job (number of years)	0.334	0.211
information on the father		
age at birth <=21	0.028	0.025
age at birth 22-35	0.829	0.864
age at birth >36	0.143	0.111
years of education	11.949	11.993
weekly hours worked[a]	40.363	40.182
time spent on child care per weekday[a]	2.235	2.288
not working (number of years)	0.196	0.198
part-time job (number of years)	0.028	0.048
full-time job (number of years)	2.775	2.754
N[a]	1047	550

[a] average at ages 0-3 of child

[b] in 1000 Euros

[c] deviant number of observations for time spent on child care (N=1032 and 537) and for type of employment (N=962 and 521)

Due to the income effect, normal good inputs such as high quality food, the number of books and toys at home or extra lessons in the afternoon will increase (if parents are altruistic at least to some degree). In our regressions, we will use family income as (the best available) proxy for goods and services inputs.

Our framework is most closely related to Leibowitz (1974) who assumes that family income has an additional direct impact on the schooling level. A similar relationship can also be derived from a production function framework that draws an analogy between the knowledge acquisition process of an individual and the production process in a firm (see, for example, Todd & Wolpin, 2003). The theory of family behavior (see Becker & Tomes, 1986, 1979 and Solon, 1999 for a simplified version) assumes that parents' intertemporal utility depends on their own consumption and on children's outcomes that are increasing in monetary investments in children. Consequently, parents invest part of their earnings in their children to maximize their own utility subject to a budget constraint. This gives the input effect. The time effect could be obtained by adding a time constraint and time investments to the model.

To begin with we estimate the following logistic regression model for a child i from family j:

$$(1)\ \Pr(high_{ij} = 1 | \underline{X_{ij}}, \underline{X_j}) = F(\beta_0 + \underline{\beta_1} \underline{X_{ij}} + \underline{\beta_2} \underline{X_j})$$

where $F(z) = \frac{\exp(z)}{1+\exp(z)}$ is the standard logistic distribution.

$High_{ij}$ is a binary variable that equals one if a child attends or has already finished high secondary track and zero otherwise. $\underline{X_{ij}}$ is a vector of characteristics that differ for different children of one family. It contains (i) child characteristics, namely a child's year of birth (normalized by subtracting 1984, the first year observed in our data) and binary indicators of a child's sex, whether a child is the firstborn child and whether a child is born between January and June[7], (ii) total net equivalent income of the household averaged over the years 0-3 of the child and (iii) time varying parent characteristics: separate indicators for whether father and mother were younger than 22 or older than 36 when the child was born as well as information on mother's and father's employment or time spent on child care at ages 0-3 of child

[7] In Germany, children born between January and June (July and December) usually enter school in autumn of the year in which they become six (seven) years old. Puhani & Weber (2007) show that children who enter school at an older age because they are born between July and December have a higher probability of attending high secondary track.

i.[8] $\underline{X_j}$ is a vector of characteristics that are shared by different siblings of one family j. It encompasses (i) household characteristics, here whether the household is classified as foreign and (ii) time invariant characteristics of parents (father's and mother's total years of education measured as schooling plus apprenticeship plus university studies) and (iii) a vector of state dummies. β_0 is a constant and $\underline{\beta_k}, k = 1, 2$ are vectors of unknown parameters.

The coefficients of interest are those of parental employment or time spent on child care. Since we control for household income, they measure the time effect of parents' employment on a child's track attendance.

To identify the true underlying coefficients we need to address potential endogeneity problems due to omitted variables. First, a child's ability is unobserved, so coefficients of explanatory variables that are correlated with ability may be inconsistently estimated. In particular, this might be the case for the effect of parental employment if parents condition their employment on their child's ability (reverse causality). To give an extreme example, parents with disabled children might not work at all. We exclude children attending Sonderschule, i.e. disabled children or children with very low ability from our analysis. Apart from these extreme cases, our identification strategy assumes that parents do not know their child's ability as long as their child is sufficiently young and, thus, cannot condition their employment decision on their child's ability. The idea is that information revelation takes time, and the amount of feedback increases only as a child grows.[9] Consequently, we exclusively use parents' labor market participation when children are aged 0-3.[10]

In the psychology literature, there is consensus that sensorimotor skills that are often used for testing intelligence in infants are not related to IQ scores obtained in later childhood (Kail, 2000). However, measures of processing speed such as habituation to novel stimuli (measured by the decrease in looking time to repeated stimuli) taken during the first year of life have been shown to be correlated with childhood IQ (see, for example, Bornstein, Hahn, Bell, Haynes, Slater, Golding, et al., 2006). In a meta-analysis McCall & Carriger (1993) find a small, but significant

[8]Averages over household income and time input information are taken over the years in which the information is available. For both household income and time input variables results are robust if we use only those observations for which information is available for all three years.

[9]Similarly, Rosenzweig & Wolpin (1995) argue that parents update their beliefs about their children's endowments as time passes.

[10]As an additional safeguard, we include parents' education as a proxy variable for their child's ability in the estimation on levels. Here, we exploit that parents' education is correlated with their own ability which in turn is partially inherited by their children.

average correlation coefficient of about 0.4 for habituation measures and later IQ. However, short-term test-retest reliability of habituation has been found to be quite low.

Unfortunately, the psychology literature remains silent on the extent to which parents can judge their children's ability at very young age. Surveying the literature on parental beliefs about their own children's cognitive development Miller (1988) concludes that parents of older preschool or school age children are moderately but far from perfectly accurate when estimating their child's ability. When parents are required to make item-by-item predictions of IQ test performance, correct predictions range from chance level to 70%.[11] Thus, our identification strategy has to assume that parents of children below age three are usually not aware that the speed of habituation to novel stimuli offers some information on their child's ability, while, for example, sensorimotor skills do not. Given that it is even hard for parents of older children to properly judge their children's level of cognitive development we deem support for our identifying assumption to be sufficient.

Second, selection of parents in the labor market is a potential problem. Imagine that parents with unobserved characteristics u_j that are either especially supportive or detrimental to raising children systematically decide (not) to work. If this were the case, the coefficients of parents' employment would not only capture the time effect that we would like to measure, but also the effect of parents' unobserved characteristics on the child's educational attainment. To control for all time-invariant unobserved parental characteristics we estimate a model on sibling differences (compare Ermisch & Francesconi, 2002 and 2001 for similar applications). Identification rests on the assumption that parents' relevant unobserved characteristics summarized in u_j (e.g. the quality of parent-child interactions) do not vary for different siblings.

To estimate a model on sibling differences we drop all observations on children without siblings from the sample. We sort all children of a family (who are born between 1984 and 1996 and for whom complete information is available) by age and build pairs of siblings. A pair consists of two adjacent siblings such that we get $n-1$ differences for n siblings. To be able to interpret our results in terms of probability of high secondary track attendance we need to estimate a binary model. For this

[11] In Miller, Manhal, & Mee (1991) only 43% of correlations of parents' prediction and children's performance are significant for 50 second and fifth grade children. In Delgado-Hachey & Miller (1993) the majority of mothers expressed a great deal of uncertainty when giving estimates of their first to sixth grade children's IQ. The correlation of estimated and actual IQ was 0.53.

purpose we construct sorted differences: first, we subtract values of all variables that belong to the older sibling from the values of the corresponding variables of the younger sibling. This results in a new differenced dependent variable that takes values -1, 0, or 1. In our sample, this differenced dependent variable is different from zero in about 20% of cases in which just one sibling attends high secondary track. Second, to be back in a binary framework we multiply all (dependent and explanatory) differenced variables of a sibling pair with -1 if the differenced dependent variable is originally -1 ("sorting"). Equation (2) illustrates this procedure for the oldest two siblings of a family in a linear probability model:

$$(2)\ \Pr\{\mathbf{1}(high_{2j} - high_{1j}) = 1 | \mathbf{1}(\underline{X_{2j}} - \underline{X_{1j}})\} = \widetilde{\beta_0} + \widetilde{\underline{\beta_1}}(\mathbf{1}(\underline{X_{2j}} - \underline{X_{1j}}))$$
$$\text{with } \mathbf{1} = \begin{cases} 1 & if \quad (high_{2j} - high_{1j}) \in \{0,1\} \\ -1 & if \quad (high_{2j} - high_{1j}) = -1 \end{cases}.$$

The numbers 1 and 2 index the first and second born sibling respectively. By construction, all explanatory variables that have the same value for siblings, i.e. u_j and $\underline{X_j}$, cancel each other out in a sibling difference estimation. Differences in parents' age at birth are collinear with the difference in years of birth and are also dropped. While the original constant term β_0 disappears due to differencing, we include a new constant term $\widetilde{\beta_0}$ to account for the effect of being sorted first (compare Ermisch & Francesconi, 2002 and Ashenfelter & Rouse, 1998). The new constant term $\widetilde{\beta_0}$ arises from differencing a dummy variable that is equal to one if a sibling is sorted first and zero otherwise. $\widetilde{\beta_0}$ captures that due to sorting the sibling sorted first in the difference has a higher probability of attending high secondary track. The interpretation of the sign, but not the level of the coefficients in the difference model is the same as in the level model. For example, imagine that we had estimated a significantly positive coefficient β_k for the effect of the difference in maternal weekly hours worked in a linear probability model. Then β_k would imply that having a mother who works one hour more when sibling 2 (sorted first) is small than when sibling 1 is small increases the probability that sibling 2 attends high secondary track while sibling 1 does not by $\beta_k \times 100$ percentage points. Hence, a positive (negative) sign still stands for a positive (negative) effect.

A more commonly used alternative to a sibling difference model is a household or mother fixed effect model (conditional logit model). In our application, a conditional logit model uses only those observations on sibling pairs in which one sibling attends high secondary track and the other one does not. In contrast, our sibling difference model also uses observations from families in which all children go to the same secondary track and estimates coefficients by comparing siblings pairs in which both siblings do or do not attend high secondary track to sibling pairs in which only one sibling attends high secondary track. We prefer estimating a sibling difference model to estimating a household or mother fixed effect model because the former uses more observations which allows estimating coefficients more precisely. Estimating a mother fixed effect model that corresponds to our main sibling difference specification in Table 6 reduces the number of observations substantially, from 301 sibling pairs to 115 single siblings. No single coefficient is significant and we cannot reject the null hypothesis that all of the model's coefficients are equal to zero (Likelihood ratio Chi-square test yields p=0.919).

5 Results

5.1 Estimation on levels

We will first present results from a logit estimation (Table 3) that does not address endogeneity problems caused by unobserved parent characteristics. The results are still a useful benchmark for comparison with other studies that use similar specifications.

While the coefficient of mother's average hours worked is not significant, the coefficient of father's average hours worked is weakly significant (p=0.080) and positive. Setting all control variables to their mean the predicted marginal effect if the father would work one hour more per week in every year is a 0.5% increase in the probability that his child attends high secondary track. Furthermore, male children are predicted to attend high secondary track less often than female children. First-born children are more likely, children born between January and June are 9% less likely to attend high secondary track. Having a young father is predicted to have an adverse effect on the child's educational attainment, having a relatively old mother seems to be supportive. Both coefficients are likely to suffer from endogeneity problems and hence might reflect unobserved parents' characteristics that are correlated with the included age intervals. The coefficients of parents' total years of education are highly significant and positive. We use state dummies to control for state specific differences in shares of students attending high secondary track.[12]

[12] Results reported in Table 3 are very robust to using mother's and father's age and age squared instead of age intervals, including year dummies instead of imposing a linear time trend or to including dummies for the number of siblings which reduces the number of observations by about 10%. Furthermore, using an ordered logit specification with a dependent variable that takes the

Table 3: Base specification: logit estimation on levels

binary dependent variable: child attends high secondary track

explanatory variables	coefficient	p-value
mother's weekly hours worked[a]	0.000	0.960
father's weekly hours worked[a]	0.019	0.080
male	-0.639	0.008
born before July	-0.380	0.095
firstborn child	0.635	0.003
year of birth - 1984	-0.006	0.889
age of mother at birth $<=21$	0.598	0.133
age of mother at birth >36	0.987	0.034
age of father at birth $<=21$	-3.822	0.000
age of father at birth >36	0.259	0.487
mother's total years of education	0.420	0.000
father's total years of education	0.348	0.000
household income[a,b]	0.086	0.927
$(\text{household income})^{2}$[a,b]	-0.080	0.785
non-German household	0.180	0.690
constant	-11.136	0.000
state dummies	yes	
N	1047	
Pseudo R^2	0.393	

[a] average at ages 0-3 of child

[b] total monthly net household equivalent income in 1000 Euros

comment: robust, clustered standard errors that allow observations to be correlated within a family

Table 4: Further specifications: logit estimation on levels

binary dependent variable: child attends high secondary track

type of employment in years	coefficient	p-value
full-time mother	-0.189	0.210
part-time mother	0.044	0.795
part-time father	-0.422	0.530
non-working father	0.200	0.352
N	962	
Pseudo R^2	0.388	

average hours spent on child care per weekday	coefficient	p-value
mother	0.050	0.156
father	-0.110	0.092
N	1032	
Pseudo R^2	0.387	

comments: robust, clustered standard errors that allow observations to be correlated within a family

Table 4 presents the coefficients of parental time inputs using hours spent on child care on a typical weekday averaged over the ages 0-3 of a child and type of employment, e.g. variables that indicate how many out of a child's first three years parents did work full-time, part-time or not at all. The omitted categories are the most common ones: working full-time for fathers and not working at all for mothers. Explanatory variables in Table 4 are the same as in Table 3. In the two additional specifications, all coefficients of parental time inputs are not significant at conventional levels.

Exploiting the manifold ways that our data offer to capture the effect of parental time inputs the overall picture that emerges in the estimations on levels is clear: parental time inputs do not seem to be a driving force of children's educational attainment.

5.2 Estimation on sibling differences

5.2.1 The sample

The siblings sample contains data on 550 siblings from 249 families. Table 2 compares means in the general and the siblings sample. The siblings sample is largely representative for the general sample. Differences in means usually occur only in the second position after the decimal point. Of course, the sibling sample contains fewer firstborn children (40% instead of 48%). On average, mothers in the siblings sample work 2.5 hours less per week and spend 0.6 additional hours per day on child care. Fathers' employment is very similar in both samples.

To control for any difference in high secondary track attendance that could be caused by birth order, our estimation will include information on which sibling is firstborn. Still, it is interesting to note that, in our sample, the probability of attending high secondary track does not differ significantly for firstborns and their siblings: it is 34% for firstborns and 32% for their siblings (a Chi-squared test yields p=0.545).

5.2.2 Kernel density estimates

To get a first impression whether differences in parental employment could be driving differences in siblings' educational attainment we estimate non-parametric Kernel

values 1 to 3 for general, intermediate, and high secondary track attendance produces estimates very similar to those reported in Table 3.

densities. The solid line depicts sibling pairs who either both attend high secondary track or both do not. The dashed line stands for sibling pairs in which one sibling attends high secondary track, but the other one does not. Again, the sibling attending high secondary track is sorted first in the difference. Figure 1 (Figure 2) displays Kernel density estimates of the distributions of differences in average hours worked by mothers (fathers) when children were aged 0-3 for these two kinds of sibling pairs. If having a mother or father with longer working hours would reduce the attendance of high secondary track we would expect the dashed line to be first order stochastically dominated by the solid line.

[Figure 1: Kernel density estimates, mother's hours worked about here]

[Figure 2: Kernel density estimates, father's hours worked about here]

Eyeballing suggests that estimated densities are very similar. Non-parametric, two-sided Mann-Whitney tests on the original distributions confirm that distributions do not differ significantly: for mothers $p_{MW} = 0.394$ and for fathers $p_{MW} = 0.740$.

Similarly, Figure 3 (Figure 4) displays Kernel density estimates of the distributions of differences in average daily hours spent on child care by mothers (fathers).

[Figure 3: Kernel density estimates, mother's time spent on child care about here]

[Figure 4: Kernel density estimates, father's time spent on child care about here]

Distributions do not differ significantly for fathers, $p_{MW} = 0.953$, while distributions of mother's time spent on child care differ marginally: $p_{MW} = 0.076$. Still, taken together the Kernel density estimates do not suggest that differences in parental time inputs are the driving force behind different levels of educational attainment.

5.2.3 Multivariate analysis

To control for differences between siblings apart from parental employment we estimate a linear probability model on sibling differences to explain different educational outcomes. The estimation requires sufficient variation in both dependent and explanatory variables. In all specifications, we have about 20% of sibling pairs in which just one sibling attends high secondary track. Table 5 and Figures 1-4 document substantial variation in mother's and father's average hours worked as well as in time spent on child care. The variation in parental time inputs across siblings does not seem to be driven by systematically different behavior towards firstborn and further children. Average differences in parents' time inputs between firstborn and further children are relatively small: on average, mothers work 6.1 hours per week when a firstborn child and 4.6 hours when their further children are aged 0-3. Mothers spend very similar amounts of time with child care when their firstborn and their further children are small (9.4 and 9.5 hours per day, the latter number refers to total, not child-specific child care time). Fathers work similar amounts per week when their firstborn children (39.4 hours) and their younger siblings (40.7 hours) are small. They spend slightly more time on child care when their first child is small (2.4 hours per day) than when the younger siblings are small (2.2 hours per day).

Table 5 shows that, by construction, variation in time inputs is largest in working hours that are measured per week, followed by hours spent on child care measured at a daily level. Variation is smallest for type of employment that is measured in years: the percentage of zero differences is very high (up to more than 90% of observations). For this reason we will provide estimates on sibling differences only for the former two measures of parental time inputs.[13]

Table 5: Variation in key explanatory variables

differenced variable	mean	standard deviation	zeros (%)	min	max	N
mother's hours worked	-.822	9.960	57.48	-40	55	301
father's hours worked	.106	10.732	17.28	-54	45	301
mother's hours spent on child care	.525	3.497	16.61	-10	19	295
father's hours spent on child care	-.167	2.008	17.63	-9	10	295
mother's full time employment	-.076	.601	86.59	-3	3	276
mother's part time employment	.007	.772	70.65	-3	3	276
non-working mother	.069	.906	65.22	-3	3	276
father's full time employment	.025	.581	87.68	-3	3	276
father's part time employment	-.007	.256	97.46	-3	2	276
non-working father	-.007	.490	90.58	-3	3	276

We prefer estimating a linear probability model on the differences over a logit (or probit) model. The reason is that with a logit or probit model the assumption that the error term has a standard logistic or standard normal distribution will either be true for the original level or the difference model. The main disadvantage of a linear

[13] In contrast, using the British Household Panel Survey data the sibling difference estimates in Ermisch & Francesconi (2002) use the difference in type of employment.

Table 6: Linear probability and probit model on sibling differences

dependent variable: sibling difference in high secondary track attendance

model	linear probability			probit	
differenced variables	coefficient	p-value	95 % confidence interval	marginal effects[a]	p-value
mother's hours worked[b]	0.005	0.105	[-0.001, 0.012]	0.005	0.073
father's hours worked[b]	0.004	0.529	[-0.008, 0.015]	0.002	0.589
male	0.009	0.715	[-0.040, 0.058]	0.016	0.488
born before July	-0.097	0.032	[-0.185, -0.009]	-0.093	0.008
firstborn child	0.151	0.003	[0.050, 0.251]	0.089	0.015
year of birth - 1984	-0.042	0.005	[-0.071, -0.012]	-0.029	0.030
household income[c]	0.019	0.961	[-0.740, 0.777]	0.032	0.928
(household income)^{2c}	0.026	0.837	[-0.221, 0.273]	0.003	0.977
constant	0.317	0.000	[0.228, 0.406]	-0.063	0.000
N	301			301	
R^2	0.240			0.251	

[a] all other explanatory variables are evaluated at their mean
[b] average per week at ages 0-3 of child
[c] total monthly net household equivalent income in 1000 Euros, average at ages 0-3 of child
comment: robust, clustered standard errors that allow observations to be correlated within a family

probability model is that it may predict probabilities larger than unity or smaller than zero for extreme values of explanatory variables. Since we are interested in the average marginal effects this should not be a major problem. Furthermore, for our baseline specification Table 6 shows that the marginal effects - especially the significant ones - predicted by an estimation on sibling differences in a linear probability model are very similar to those obtained in a probit model. As further robustness checks we have also estimated the baseline specification in Table 6 when using data on non-foreign West-Germans (subsample A) only or when using school track information at age 14 (instead of latest available information) as dependent variable. The resulting magnitudes and significance levels of coefficients are very similar to those of the baseline specification.

Table 7 contains the coefficients from three different specifications. Specification

A uses observations from families in which both parents are present (in our data) and information on both parents' time inputs is completely available. As do most studies on the relationship between parental employment and children's educational attainment, specification B does not include information on fathers. Hence, it additionally includes observations from families with single mothers and families with present fathers on whom information is incomplete. We add a dummy variable for absent fathers that turns out not to be significant. Specification C adds a dummy variable that takes a value of one if the father is present and zero otherwise and reports coefficients of father's time inputs when time inputs are interacted with this dummy.

Results in Tables 6 and 7 show that differences in father's employment do not contribute significantly to explaining differences in educational attainment. The coefficient of differences in mother's hours worked is positive and marginally significant (in Table 7, p=0.105 in specification (A) and (C) and p=0.085 in specification (B)). This contrasts the results of Ermisch & Francesconi (2002), the only other study that uses sibling difference estimates to investigate the effect of parental time inputs on children's educational achievements and finds an adverse effect of mother's full-time employment. The precision of our baseline estimate (specification (A)) implies that we can statistically rule out that having a mother who works one hour more per week (when the sibling sorted first was young than when the second sibling was young) lowers the probability that the sibling who is sorted first attends high secondary track (while the second sibling does not) by more than 0.1 percentage points, an economically negligible number. The alternative specifications in Table 7 show that average parental time spent on child care does not influence attendance of high secondary track significantly.[14] In sum, our sibling difference estimates suggest that parental time inputs are not decisive for a child's educational attainment. If there is any effect at all mother's hours worked seem to have a modest positive effect on educational achievements.

To document the power of our estimation we have also run power calculations based on our sample size (N=301) and the standard deviation of estimated time input coefficients. For mothers' (fathers') hours worked in specification A we would detect a significant difference using a 95% significance level with at least 90% probability if the true coefficient was larger than 0.0106 (0.0180) or smaller than -0.0106 (-0.0180). Power calculation results for hours worked in specifications B and C are

[14] Results in Table 7 are robust to adding a squared term for mother's and father's time inputs.

very similar. Thus, our data provide enough power to predict small effects significantly. For mothers' time spent on child care at a typical weekday we would detect a significant difference using a 95% significance level with at least 90% probability if the true coefficient was larger than 0.0308 (0.0232, 0.0264) in specification A (B, C). For fathers, the corresponding numbers are -0.0546 in specification A and -0.0534 in specification C.

Further evidence of the predictive power of our estimates is that they predict children who are born between January and June to be less likely and firstborn children to be more likely to attend high secondary track. The advantage of firstborn children decreases with each year they are apart from the second born sibling. For the average age difference of siblings in our sample (2.13 years), we reject the hypothesis that firstborn children are more likely to attend high secondary track (p=0.359). In contrast to the level estimation, the sex of a child is no longer significant. As Tamm (2008) we do not find a causal relationship between household income and high secondary track attendance.

For some explanatory variables, the significance levels and, thus, implications from the level and difference estimation differ markedly, e.g. in contrast to the level estimates, the sibling difference estimates document a modest positive effect of maternal hours worked. Table 2 documents that differences are not caused by different sample characteristics. This suggests that controlling for unobserved parent characteristics affects results and should become the standard in the literature on the effects of parental employment on children's educational attainment.

Furthermore, mother's and father's time inputs do not influence children's educational outcomes in different ways: we can reject the hypothesis that the coefficients of mother's and father's employment and time spent on child care differ significantly (F-tests for specifications (A) in Table 7 yield F=0.09, p=0.763 for hours worked and F=0.33 and p=0.565 for time spent on child care). Estimating the baseline specification in Table 6 but substituting mother's and father's hours worked or time spent on child care with parents' joint working hours or joint time spent on child care yields coefficients of 0.004 (p=0.180) or -0.007 (p=0.353), respectively. Since the coefficients of joint time inputs are not significant, they confirm our previous results.

Additionally, we have analyzed whether the effect of parental employment differs at different ages of the child, in our case at age 1, 2, and 3. Some studies that focus on children's short term outcomes have found that maternal employment during the first year of a child is especially detrimental. For example, Ruhm's (2004) and

Waldfogel, Han, & Brooks-Gunn's (2002) results imply that maternal employment during the first year of a child reduces math, reading and verbal achievement test scores at the ages 3-8 substantially. Our results on long-term outcomes are not consistent with this finding. In contrast, the coefficient of maternal working hours during the first year is positive (0.004) and marginally significant (p=0.082). The other year-specific coefficients of maternal and paternal hours worked or time spent on child care are not significantly different from zero. F-tests for equality of coefficients document that each parent's coefficients do not differ across the ages 0-3 of a child. This justifies our approach of averaging time input information over the first three years.[15]

6 Concluding remarks

This paper has analyzed whether parental employment affects children's educational attainment. We have explicitly addressed potential endogeneity problems: to control for unobserved time-invariant parent characteristics we have used estimates on sibling differences. To avoid inconsistent estimates due to reverse causality we have dropped disabled children from the analysis and have focused exclusively on parental employment when children are young (aged 0-3) such that signals about ability are still scarce.

Some caveats still apply to our analysis: first, we cannot be sure about the external validity of our results that are based on a sample of siblings for single children. While we are not aware of an obvious reason why parental employment should affect single children in a systematically different way than children with siblings, we cannot proof that our results apply to single children as well.

Second, our analysis cannot control for unobserved time-variant parent characteristics. For example, our analysis assumes that one parental hour spent on child care has the same effect for different siblings. This assumption could be violated in both possible directions: on the one hand, the quality of parent-child interactions could increase the more experienced parents are; on the other hand, parents with

[15] For the three coefficients of mother's (father's) hours worked F=1.02 and p=0.364 (F=0.41 and p=0.666), for the three coefficients of mother's (father's) time spent on child care F=0.54 and p=0.586 (F=0.06 and p=0.939). Furthermore, in both specifications all six parents' coefficients do not differ significantly (F=0.58 and p=0.713 for hours worked and F=0.42 and p=0.832 for time spent on child care, respectively). The complete estimation results are available from the authour upon request.

more children could, for example, be stressed more heavily or distracted more often which could lower the quality of time that they spend with their children.

Third, assuming that siblings' abilities are correlated parents may learn something about a younger child's ability by observing an older sibling. This may result in inconsistently estimated coefficients of parental time inputs if (and only if) parents condition the time they devote to their younger child on what they have learned about his ability by observing his older sibling. Whether the true underlying effect of parental time inputs on a child's educational attainment is over- or underestimated depends on the interplay between the sign of the correlation between parental time inputs and a child's ability[16] and on the sign of the true underlying effect. For example, assume an increase in parents' hours worked increases the probability of high secondary track attendance. Then, a negative (positive) correlation between parents' hours worked and their child's ability (after controlling for parents' time-invariant ability) would result in an underestimated (overestimated) effect of parental time inputs on high secondary track attendance.

Furthermore, our measures of parental time inputs exclusively capture quantity, not quality - though quality is controlled for in the sibling difference estimates to the extent quality of parent-child interactions does not differ for different siblings. Due to lack of data, we have not controlled for non-parental time and good inputs and have ignored potentially important differences between different kinds of non-parental child care (such as attendance of Kindergarten, child care by relatives or nannies). These are important issues left for future research. Still, it is often argued that parental employment patterns per se shape a child's environment and outcomes. This is what we have tested for.

In sum, our results do not support worries that parental employment is detrimental for children's educational attainment. The core of our analysis are the estimates on sibling differences that use average weekly working hours when the child is aged 0-3 to measure parental time inputs: given their precision, we can statistically rule out that having a mother who works one hour more per week lowers the probability of high secondary track attendance by more than 0.1 percentage points, an economically negligible number. Actually, all coefficients of maternal employment are positive, but not significant at conventional significance levels (though at an 9 to 11% level). The corresponding coefficients of paternal employment and estimates using parental time spent on child care instead of working hours are not significant.

[16] This holds if a child's ability is not correlated with any other explanatory variables than parental time inputs.

Thus, our results clearly rule out a negative time effect of parental employment. But we do not find evidence for a positive income effect either, i.e. a higher family income does not increase a child's educational attainment. Taken together, our results imply that it is not parental employment or quantity of parent-child interactions that are decisive for children's educational attainments, but, for example, birth order within a family, age relative to classmates or parental characteristics.

With respect to the current debate about the expansion of day care facilities in Germany our results do not suggest that a more comprehensive child care infrastructure will hurt children's future prospects by raising maternal employment. Of course, our estimates are based on data from the past. To some extent, the current reforms will lead to changes in the institutional environment and perhaps also society's attitudes towards working mothers that may affect the interplay between parental employment and child outcomes.

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Table 7: Further specifications: linear probability model on sibling differences

dep. var.: sibling difference in high secondary track attendance

coefficients of difference in hours worked, average per week

specification	(A)	(B)	(C)
mother	0.005	0.006	0.005
	(0.105)	(0.085)	(0.105)
father	0.004	-	0.003
	(0.529)	-	(0.582)
N	301	372	345
R^2	0.240	0.307	0.321

coefficients of difference in time spent on child care, average per weekday

specification	(A)	(B)	(C)
mother	-0.003	-0.003	-0.002
	(0.747)	(0.688)	(0.772)
father	-0.016	-	-0.012
	(0.361)	-	(0.478)
N	295	361	338
R^2	0.239	0.293	0.314

comments: robust, clustered standard errors that allow observations to be correlated within a family; p-values are reported in brackets
(A): uses only observations with complete information on both parents
(B): uses all observations with complete information on mother
(C): estimates coefficients of father's age, education and time inputs conditional on father being present