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Paternal unemployment during childhood: causal effects on youth worklessness and educational attainment

Steffen Mueller
Regina T. Riphahn
Caroline Schwientek

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Friedrich-Alexander-University Erlangen-Nuremberg

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**Paternal unemployment during childhood:
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Steffen Müller

Regina T. Riphahn

Caroline Schwientek

University of Erlangen-Nuremberg

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Using long-running data from the German Socio-Economic Panel (1984-2012) we investigate the impact of paternal unemployment on child labor market and education outcomes. We first describe correlation patterns and then use sibling fixed effects and the Gottschalk (1996) method to identify the causal effects of paternal unemployment. We find different patterns for sons and daughters. Paternal unemployment does not seem to causally affect the outcomes of sons. In contrast, it increases both daughters' worklessness and educational attainment. We test the robustness of the results and explore potential explanations.

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Correspondence to:
Regina T. Riphahn
Univ. of Erlangen-Nuremberg
Lange Gasse 20
90403 Nuremberg, Germany
Phone: +49 - 911 - 5302 826
Fax: +49 - 911 - 5302 178
Email: regina.riphahn@fau.de

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1 Introduction

The economic literature shows that educational choices and the early experience of unemployment can affect lifetime labor market opportunities (e.g., Card 1999, Gregg 2001, Schmillen and Umkehrer 2013). Youth unemployment is a pressing labor market problem in many countries; currently, many European economies face youth unemployment rates well beyond twenty percent. In this situation, commentators not only discuss the risks of poverty but also emphasize how emigration and lack of opportunities for the young may endanger societies. Fortunately, youth unemployment is low in Germany but the country faces traditionally low enrollment in tertiary education (OECD 2014). While the importance of youth unemployment and of low participation in tertiary education are undisputed, their causes are not fully understood. In this paper, we analyze if and how paternal unemployment affects these outcomes. The literature has not paid much attention to the potentially 'hidden cost' of paternal unemployment that may work through its intergenerational transmission. If such effects exist labor market policy may also have to attend to parents when addressing youth unemployment and low educational attainment.

Various mechanisms may relate paternal unemployment and youth labor market and education outcomes. They include observable and unobservable characteristics that run in the family as well as true causal effects of paternal unemployment on child outcomes. Observable characteristics such as region of residence or social networks are correlated across generations and may affect employment and education. Similarly, unobserved determinants of labor market outcomes, such as preferences for industries or occupations, but also ability, motivation, attitudes, beliefs, or personality traits may be shared between parents and children.

To derive appropriate policy recommendations it is crucial to disentangle the causal effect of paternal unemployment from the influence of shared characteristics. A causal channel exists if the experience of paternal unemployment changes a youth's probability of worklessness or educational attainment. The experience of paternal unemployment may affect how children perceive unemployment and how they value education. The direction of the causal effect on youth unemployment is a priori unclear: paternal unemployment may reduce the stigma associated with becoming unemployed but it may also increase the time that parents can invest in their children. The effect on educational attainment should be positive if children start to consider education as insurance against unemployment or as a door-opener for a successful career. However, if paternal unemployment reduces household income and increases parental stress this may limit child educational opportunities, e.g., due to lower self-esteem and confidence or to family liquidity constraints which render the funding of post-secondary education difficult.[1]

Studies on the intergenerational transmission of unemployment (e.g., Eckhaugen 2009, Gregg et al. 2012, Maeder et al. 2014, Macmillan 2014, O'Neill and Sweetman 1998, Oreopoulos et al. 2008) typically report positive intergenerational correlations of unemployment but mixed results on whether there is a causal effect. While the literature analyzing educational outcomes finds negative short-term effects of paternal unemployment (e.g., Rege et al. 2011, Gregg et al. 2012, Pinger 2012), evidence on longer-run effects exists only for Canada and the U.S. (Coelli 2011, Wightman 2012) and points at a negative causal effect. Given the very different education systems, in particular with respect to the funding of post-secondary education, it is unclear whether the effect on educational outcomes is also negative in Germany.

We are the first to offer evidence for the German case on the long-run effect of paternal unemployment on offspring's educational attainment in general and for daughters specifically. Germany is particularly interesting as, on the one hand, the OECD advised to increase enrollment in tertiary education (OECD 2012) and, on the other hand, Germany faces low youth

[1] The latter argument touches the debate about possible credit constraints on post-secondary education attendance (e.g., Cameron and Taber 2004). Such financial constraints might be more severe in countries with tuition fees, such as the U.S., than in Germany where tertiary education is generally free and costs mainly consist of foregone earnings.

unemployment. We take advantage of long running panel data from the German Socio-Economic Panel (SOEP) to investigate correlation and causation patterns. Fixed effects techniques and the Gottschalk (1996) method identify causal relationships.

We contribute to the literature in a number of ways. First, this is the first study on the long-run effect of paternal unemployment on educational attainment for Europe. Second, we provide the first study on the intergenerational transmission of unemployment for daughters for Germany. Third, by looking at unemployment and education in one study, we provide a more complete picture on the effect of paternal unemployment. Fourth, given the (mostly data driven) variety in the definition of treatment age in previous studies, we provide systematic evidence on whether effects of paternal unemployment on offsprings' outcomes vary by treatment age.

Our results show the expected correlation patterns: youth worklessness correlates positively and educational outcomes correlate negatively with earlier paternal unemployment, identically for both sexes. The correlations for sons increase if fathers' unemployment occurred later during childhood. The differences in correlation patterns across treatment age are less systematic for daughters but suggest higher correlations of education outcomes if paternal unemployment happened in earlier childhood. After accounting for time-invariant family characteristics the effects of paternal unemployment differ for sons and daughters. Paternal unemployment does not causally affect sons' outcomes. In contrast, it tends to increase daughters' risk of worklessness as well as their educational attainment. Possible explanations of the latter surprising result may relate to risk aversion, marriage markets, or maternal role models which differentially affect the education response of boys and girls to paternal unemployment. We investigate these mechanisms and provide robustness tests.

The structure of this paper is as follows. We first summarize key findings of the literature. Section 3 describes our empirical methods. Section 4 presents the data and section 5 shows the empirical results. We then offer robustness tests of our findings and discuss potential explanations for observed gender differences in sections 6 and 7. Section 8 draws conclusions.

2 Literature

2.1 Intergenerational transmission of unemployment

There are only few studies on the intergenerational transmission of unemployment.[2] Johnson and Reed (1996), Macmillan (2010, 2014), Mäder et al. (2014), and O'Neill and Sweetman (1998) study the effect of *paternal* unemployment on sons, whereas Eckhaugen (2009) analyzes the effect of *parental* unemployment on sons and daughters. The studies differ in various ways: Johnson and Reed (1996), Macmillan (2010 and 2014), and O'Neill and Sweetman (1998) use data from the U.K. where they observe paternal unemployment only at sons' age 10, 11, 12, or 16. The U.K. studies' definition of sons' outcome period spans from the end of full time education up to age 33. Mäder et al. (2014) use German data and define the treatment period as sons' age 10-15 and the outcome period from 17 to 24. In Eckhaugen's 2009 study of Norwegian siblings the older (younger) sibling was born 1972/73 (1978/1979) and treatment (outcome) age is 14-18 (24-26). Despite these differences, all papers find positive intergenerational correlations but little evidence for a causal effect.

Studies utilizing parental job displacement due to mass layoffs and plant closures also yield positive correlations. Oreopoulos et al. (2008) and Gregg et al. (2012) find a higher unemployment risk for children of displaced fathers in Canada and the U.K., respectively. If mass layoffs and plant closures are truly exogenous events, i.e., unrelated to family background, these findings have a causal interpretation. Given the variety of empirical approaches and definitions of core variables and the small number of studies, additional evidence on the intergenerational transmission of unemployment is helpful.

2.2 Parental unemployment and educational outcomes

[2] There is a much larger literature on the intergenerational transmission of welfare receipt (e.g. Antel 1992, Gottschalk 1996, Edmark and Hanspers 2011).

Although a number of papers explore the relationship between parental unemployment and offspring's education, only few look at long-term effects. Instead, most study short-term school performance effects. Ananat et al. (2008), Rege et al. (2011), and Gregg et al. (2012) find a detrimental effect of parental unemployment on offspring's school grades for the U.S., Norway, and the U.K., respectively. Stevens and Schaller (2011) report an increased propensity to repeat grades for U.S. pupils and Andersen (2013) shows that U.K. children lower their schooling ambitions during parental unemployment. Finally, Pinger (2012) finds that paternal unemployment when the child is 16 years old reduces the probability of upper secondary school choice in Germany. While this literature agrees that there is a causal short-run effect, little is known about how paternal unemployment during childhood affects educational outcomes in the longer run.

We found only two causal studies on medium- or long-run effects. Coelli (2011) uses parental job displacements when the offspring is aged 16-18 and reports a decreased probability of enrolment in tertiary education by age 20 in Canada. Wightman (2012) follows the same identification strategy and finds that experiencing a parental job loss during childhood reduces the probability of obtaining any post-secondary education by age 21 in the U.S..

3 Empirical model and methods

3.1 The model

The two labor market outcomes analyzed in this study are youth worklessness and educational attainment. Empirically, we study both outcomes separately, however, in this methodological discussion we refer to both jointly as "labor market outcomes". We regress offsprings' labor market outcome in the observation period (*t1*) on fathers' unemployment experience in a previous period (*t0*) (and a vector of controls).[3,4] The estimates yield whether the next generation's labor market outcomes vary with paternal unemployment. These correlations can only be interpreted as the causal effect of fathers' unemployment history if the latter is uncorrelated with the error term in the children's outcome equation. This is unlikely because the reasons for fathers' and offsprings' labor market experiences may have a common component shared by all members of the family. Family background may include similar tastes and preferences concerning education and work but also biological factors or ability. Consider the following model:

$$y_{cit1} = un_{fit0}\beta + x'_{cit1}\gamma + \varepsilon_{cit1} \qquad (1)$$

$$un_{fit0} = x'_{fit0}\delta + \varepsilon_{fit0} \qquad (2)$$

where c denotes children, f fathers, i families, *t0* and *t1* refer to the past and ongoing time periods, and β, γ, and δ are parameter vectors. Children's outcomes y_{cit1} are affected by fathers' unemployment experience in *t0* (un_{fit0}) and a vector of controls (x_{cit1}). The error terms are defined as

$$\varepsilon_{cit1} = \alpha_{ci} + \tau_{cit1} \qquad (3)$$

and

$$\varepsilon_{fit0} = \alpha_{fi} + \tau_{fit0}. \qquad (4)$$

τ_{cit1} and τ_{fit0} are white noise errors with zero covariance. If family background is relevant for paternal unemployment and child outcomes, then we expect $corr(\alpha_{ci}; \alpha_{fi}) \neq 0$. This correlation generally biases the OLS estimates of β in equation (1). The biased estimates mix the effects of family background and paternal unemployment. The challenge is to disentangle the causal part from the influence of family background. Both effects are interesting but have different policy implications. We use a fixed effects method and the Gottschalk (1996) approach to separate

3 In our empirical analysis we consider children's age 10-15 to represent period *t0*, and children's age 17-24 to represent *t1*.

4 The causal effect of maternal unemployment may be of interest as well. We focus here on paternal unemployment only, because in the framework of the German family tradition of the last decades hardly any mother worked full-time and a high share was out of the labor force while caring for children. Here, the meaning of unemployment differs for the prototypical mother compared to that for the prototypical father, i.e., the bread-winner of the family.

family background and true causal effects. The main advantage of the two methods is that they do not rely on exclusion restrictions or instruments for identification. Next, we provide more detail on the two approaches.

3.2 Sibling fixed effects

A natural way to eliminate the influence of family background is to compare the outcomes of siblings. Ekhaugen (2009) compares siblings who were at different ages at the time of parental unemployment. Assuming there is an age after which parental unemployment no longer affects child employment outcomes, sibling differences can net out the effect of family background. In our main specification we assume that children are affected by parental unemployment if they are aged 10 to 15.[5] The definition of a treatment age is important as the sibling fixed effects approach identifies the effect by comparing the outcomes of siblings where one experienced a paternal unemployment spell during treatment age and the other did not.[6]

We now discuss drawbacks of the method and start with the consequences of using an invalid treatment age window. As in Ekhaugen (2009), we exclude sibling pairs where the older sibling has been treated. This circumvents the problem that paternal unemployment may *permanently* change the family in a way that affects also the younger sibling although he or she did not experience the treatment during treatment age. If, however, our treatment age window is wrong in the sense that older siblings are affected despite being already age 16 or older, the fixed effects approach will generally yield estimates biased towards zero as the observed outcome difference between the siblings is then smaller than under a correct age window. A second and more obvious drawback of the fixed effects approach is that only individuals with

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5 The literature uses similar definitions. While our outcome age (*t1*) reflects the definition of youth unemployment (17-24 years) and the typical school leaving age from the lower secondary track, the choice of treatment age (*t0*) of 10-15 is arbitrary. We test the sensitivity of our results using alternative age groups.

6 Literally, the treatment age definition implies that also sibling pairs where one is 15 and the other is 16 at the time of paternal unemployment contribute to identify the effect. We test whether our results are robust to imposing a minimum age distance between siblings.

siblings enter the sample.[7] Finally, if paternal unemployment is triggered by an event that also changes the younger child's labor market prospects this can invalidate the fixed effects approach.

In sum, the fixed effects approach identifies the causal effect by comparing children treated when aged 10-15 with their siblings who are older at the time of paternal unemployment. The sibling-pairs approach implies that families with more than two children can enter the sample more than once. For instance if all children of a family with three children are observed during treatment and outcome period, up to three different pair combinations for that family can be used.

3.3 The Gottschalk Method

Based on Gottschalk (1996) we add future paternal unemployment to equation (1) yielding:

$$y_{cit1} = un_{fit0}\beta + un_{fit2}\alpha + x'_{cit1}\gamma + \varepsilon_{cit1} \qquad (5).$$

We assume that paternal unemployment in period *t2* (e.g., when the offspring is aged 25-30) has no causal impact on child's earlier outcome in *t1*. In that case α captures only family background and subtracting it from the coefficient of prior paternal unemployment (β) yields the causal effect of interest simply using an OLS regression. While Gottschalk (1996:4) points out that this is true only if child outcomes do not affect later paternal outcomes, Ekhaugen (2009:101) notes that it must additionally be assumed that parents becoming unemployed after their offspring reaches the critical age (in *t2*) are not systematically different from parents becoming unemployed before (in *t0*). One advantage of the Gottschalk (1996) method over the fixed effects approach is that also individuals without siblings can be considered. The second advantage of using the Gottschalk (1996) approach along with the fixed effects approach is that

[7] In tests based on simple linear regressions we found that generally the patterns do not differ significantly for children with and without older siblings.

both methods have different strengths and weaknesses. Evidence supported by both methods is therefore more credible.

Our empirical analysis proceeds in several steps. First, we study the correlation of youth outcomes with earlier paternal unemployment. Then we investigate the sensitivity of these correlations to the choice of treatment age. Next, we study causal effects using Gottschalk and sibling fixed effects methods before we investigate the robustness of our results. Finally, we discuss possible explanations of our findings.

4 Data

4.1 Sample

Our analysis exploits data from the German Socio-Economic Panel (SOEP), a longitudinal survey conducted annually since 1984 (Wagner et al. 2007) where we use all annual waves (1984-2012). The advantage of the SOEP is the long observation period and the availability of detailed information on family background and labor force status. We can use retrospective biographical as well as annually collected survey information. Compared to administrative data the SOEP offers relatively small samples. The SOEP data overcome an important drawback of administrative data: they cover all unemployed persons, independent of whether they are officially registered. This is particularly appropriate for an analysis of youth unemployment.

Our sample considers male and female respondents at age 17-24, i.e., in period *t1*. We omit individuals with an immigrant background; females who give birth are omitted from the sample in the year of the birth (about six percent of the female sample). We drop observations with missing information on the dependent variables which describe labor force status and educational attainment. We have to omit observations on individuals who cannot be matched to information on paternal unemployment. This generates samples of about 2,200 observations on sons and daughters each for the correlation analyses.[8] In the analyses applying the Gottschalk (1996) method we additionally have to condition on observing paternal unemployment at least once when the child is aged 25-30. This reduces sample sizes to about 900 observations for either sex. In the fixed effects estimations we use sibling pairs where the younger sibling experienced paternal unemployment in the relevant age and the older sibling did not. Our samples here comprise up to 1,800 observations for either sex depending on the outcome examined.

The additional information that can be gained from a panel structure is limited because the key explanatory variable – fathers' unemployment during childhood – does not vary over time. Consequently, considering panel data would shift weights in favor of individuals who are observed more often in the considered age range (17-24). As non-response and panel attrition at this age are potentially selective, we prefer to use each person only once in the estimation sample and control for the occurrence of missing values by using appropriate indicator variables.

4.2 Key variables

We use six different dependent variables to measure employment and education outcomes for sons and daughters. Our two employment measures indicate (a) whether the youth ever experienced worklessness between ages 17 and 24, i.e., the age range considered in the definitions of youth unemployment, and (b) the observed number of years of worklessness in the considered age range. Individuals are considered to be workless if they are either registered unemployed, or not employed; individuals are not considered to be workless if they are in vocational training, in academic education, in the military or in substitute service. We apply a

8 Generally, our sample sizes vary slightly across outcome variables due to missing values.

broad unemployment measure because young individuals may not officially register as unemployed when they actually are.[9]

We code four measures of youth educational attainment: (c) in the tracked German secondary education system it matters whether a pupil attends and completes the highest upper secondary school track, because this is the only direct access to tertiary education. Therefore we use one indicator to describe whether a youth was observed to attend upper secondary school at any time between ages 17 and 24. (d) Separately, we investigate whether the individual graduated from upper secondary school by age 21-24.[10] (e) Another dichotomous indicator describes whether the person is observed to attend college between ages 21 and 24. (f) Our final educational attainment measure consists of the number of years of education as of age 22.[11]

As our key treatment indicator we use the annual self-reported unemployment status of the father at the time of the interview in the years when the child was aged 10-15. In contrast to the worklessness measure that we apply for sons and daughters we apply a stricter definition of paternal unemployment and only use reports of registered unemployment at the time of the interview. We apply a binary indicator of whether the father was ever observed to be unemployed at age 10-15 of the child.

Table 1 presents descriptive statistics for our six dependent variables separately for sons and daughters and by paternal unemployment background. On the extensive margin about one in five youths experienced an episode of worklessness and on the intensive margin we observe about 0.3 observation years in worklessness across the full sample. While gender differences are small we observe substantial differences between offspring of fathers with and without prior unemployment experience: children of previously unemployed fathers are about seventy

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[9] About sixty percent of the worklessness events of the youths in our data reflect registered unemployment.

[10] As the regular upper secondary school graduation age for our cohorts was 18-19, the vast majority should have completed secondary school by age 21-24.

[11] We estimated our models for years of education at all age years and randomly limit ourselves to present the results observed for age 22.

percent more likely to experience a worklessness event and they experience more years in worklessness than children of fathers who were never unemployed.[12] With respect to educational outcomes we observe higher levels of educational attainment among daughters than among sons. In both subsamples children of previously unemployed fathers feature in part substantially lower educational attainment. About ten percent of the youth in the full samples experienced paternal unemployment spells.

4.3 Model specification

We present our estimation results for a parsimonious basic and an extended model specification. Due to missing information we do not observe all fathers and children in all survey years. In the basic model we control for indicators of missing values on child and father observations in order to avoid biases due to selective survey participation.[13] The estimation results for β obtained from this basic specification reflect unconditional correlations.

In our extended specification we account for characteristics that may be correlated with the effect of paternal unemployment. For the child we consider year of birth, birth order, and the federal state of residence at age 17 to account for regional labor market characteristics.[14] As labor market outcomes may be subject to seasonality we consider fixed effects for the calendar month of the interview. We further control for year of birth, education, and occupation for both parents and for the number of persons and the number of siblings at the household level; to reflect state level differences in the education system we account for the share of a person's birth cohort holding an upper secondary school degree; it varies by state and over time. Finally, we consider fixed effects for fathers' state of residence when first interviewed to account for the

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12 These numbers are in line with O'Neill and Sweetman (1998:438) who report for the U.K. that sons of previously unemployed fathers are about 90 percent more likely to be unemployed themselves compared to sons of fathers who were not been unemployed before.

13 Our sample consists of youths born between 1969 and 1995. With 2012 as the most recent survey year the younger birth cohorts are observed for fewer years; we additionally control for a variable that reflects the maximum number of observation years by birth cohort.

14 The year of birth jointly accounts for cohort effects and a time trend.

regional labor situation at that time. The Appendix presents descriptive statistics on the covariates.

The literature on the short-run effects of paternal unemployment discusses the role of income shocks (e.g., Rege et al. 2011). We do not consider income effects for several reasons: first, in our framework the relevant unemployment shock can occur 14 years prior to the outcome measure. It is not obvious how an income shock can be operationalized in this situation. Second, the German unemployment insurance generally offers earnings replacements of up to 67 percent for at least one year and reduced benefits afterwards. Therefore, the magnitude of unemployment related income shocks is likely to be limited. Third, secondary and tertiary education in Germany is typically free of charge and the government offers financial support to students in need. Therefore, also the relevance of liquidity constraints should be lower than in other countries. Finally, we omit controls for household income in order to avoid endogenous indicators of post-unemployment parental employment choices in our model.

5 Results

5.1 Correlation analysis

As step one of our analysis we study the correlations between paternal unemployment experience and child worklessness and education outcomes. We estimate our models separately for sons and daughters and use the parsimonious basic and the extended specifications. **Table 2** shows the estimates for β with standard errors clustered at the level of the father.

The first two rows depict intergenerational unemployment correlations. All estimated coefficients are positive which confirms findings in the international literature. The coefficients decline in magnitude and statistical significance once control variables are considered in the extended specification; however, the correlations remain positive. We find no clear gender differences. The bottom rows describe the correlations between education outcomes and paternal unemployment, which are mostly negative; thus, children of fathers who experienced unemployment tend to attain lower levels of education compared to children of fathers who were not unemployed at the children's age 10-15. The coefficients decline in magnitude and statistical significance is lost once control variables are considered in the extended specification. The negative correlations are slightly larger for sons than for daughters. The patterns match the international evidence.

5.2 Relevance of treatment age

An advantage of our long running panel dataset is that we are flexible regarding the definition of relevant age ranges. In contrast, other authors often can use only few calendar and age years. We take advantage of this data situation and investigate the relevance of the age at which the child experiences paternal unemployment. In addition to our baseline definition, where we consider paternal unemployment when the child is aged 10-15, we consider the correlation patterns of paternal unemployment at age 8-13 and age 12-17. **Table 3** shows the estimation results for the extended specification of our linear models for sons and daughters.

The general correlation patterns are stable across alternative treatment age regimes for sons and daughters, with positive worklessness and mostly negative education correlations. The relevance of the treatment age appears to differ for sons and daughters: for sons the correlations between child outcomes and paternal unemployment are more pronounced and more statistically significant if paternal unemployment occurs at later ages whereas for daughters correlations are more pronounced if fathers were unemployed at a younger age. **Table 3** shows the results for all available observations at each age range; the gender difference in treatment age patterns holds up even if we restrict the three subsamples to only those individuals who are observed in each of the three age groups.

To our knowledge this type of gender difference has not been shown before. Only Wightman (2012) tested the relevance of treatment age for parental unemployment on child educational outcomes before. He reports for a gender mixed sample of youth that the negative correlation between paternal unemployment and child education is larger if unemployment occurred at age 6-12 relative to age 13-17. This appears to agree with our findings for daughters but not for sons.

Overall, we find differences in the magnitude of the correlations but – at least among the statistically significant results – not in their nature and direction. Therefore, we follow the literature and focus on the middle treatment age (10-15) for our study of causal treatment effects. We investigate the heterogeneity of treatment effects across treatment ages in a robustness test.

5.3 Causal effects based on the Gottschalk (1996) and the fixed effects method

Next, we discuss the causal effect of paternal unemployment on child outcomes. **Table 4.1** shows the results of the Gottschalk (1996) approach, i.e., the difference between the two coefficient estimates for paternal unemployment in equation (5), β - α. We present the results based on the extended model specification separately for sons and daughters. The causal worklessness effects are negative for sons and positive for daughters. However, no estimate is statistically significant. We therefore we find no causal effect of paternal unemployment on youth worklessness.

The causal effects on education outcomes are negative and partly insignificant for sons. The patterns for the education outcomes of daughters differ. Here three out of four coefficients are positive and statistically significant. This surprising result suggests that daughters obtain more education if their fathers experienced unemployment.

We use sibling fixed effects estimation to determine whether the causal effects obtained with the Gottschalk method can be confirmed under a different set of identifying assumptions. **Table 4.2** shows the estimates. With the fixed effects controls, the extended specification does not consider the covariates that vary at the level of parents or the household and are identical within sibling pairs. Instead, we account for child year of birth, birth order, gender (identified by the older sibling), and the state education variable in addition to the set of missing value indicators that we also applied in the basic specification.

The results confirm those obtained using the Gottschalk approach: we obtain no significant causal effects of paternal unemployment for sons. For daughters we continue to find some evidence for significantly higher worklessness in response to paternal unemployment. More surprising is the clear pattern of mostly significantly better education outcomes for daughters of fathers who experienced unemployment. The fixed effects results confirm the Gottschalk outcomes in **Table 4**. The probability of attaining an upper secondary school degree increases by more than 30 percentage points and the total number of years of education by age 22 by about half a year relative to the older sibling that did not experience paternal unemployment when young. We discuss possible explanations of these findings after investigating their robustness.

6 Robustness tests

We performed a number of tests to determine the robustness of our results. First, in order to test for the relevance of measurement error we redid the correlation, Gottschalk, and fixed effects analyses considering only those observations of male and female youths for whom we had at least 3 valid father observations in period *t0*. The sample size drops by about 20 percent. The results do not deviate qualitatively from the patterns presented above (available upon request).

Second, we dropped observations of females who gave birth while they were aged 17-24. The share of young mothers is rather small (about six percent) and omitting them does not affect the results (available upon request).

Third, as the fixed effects results are identified only based on 17-24 year olds who have an older sibling we tested in the correlation and Gottschalk approaches whether children without siblings respond differently to paternal unemployment compared to children with siblings. The least squares estimations yield almost exclusively statistically insignificant and small effects of the interaction between paternal unemployment experience and a single child indicator (available upon request). To determine the robustness of the causal effects estimations with the Gottschalk approach, we added single child indicators and their interactions with paternal unemployment in periods *t0* and *t2* to the Gottschalk specification and tested (i) whether the coefficients for the additional paternal unemployment interactions are jointly significant and (ii) whether the causal effect (i.e., $\beta - \alpha$) differs significantly for children with and without siblings. The results yield that there are no differences in the causal response patterns for sons with and without siblings (across all outcomes and both tests). For daughters we find significant coefficient and causal effect differences with respect to worklessness but not with respect to education outcomes. In particular, the results suggest that for single daughters the positive causal effect on worklessness is substantially and significantly smaller (even negative) than for daughters with siblings.[15] This suggests that all fixed effects results for sons and the fixed effects results on education outcomes for daughters are reliable beyond the subsample of children with siblings from which they are identified.

Fourth, the results hold up to modifications in the specification in the empirical model. As an example, we estimated without controls for maternal characteristics, and for alternative sets of state fixed effects. The reported findings are robust to these modifications (available upon request).

Fifth, we ran method-specific robustness tests. When we applied the Gottschalk method only to those observations for which we observed at least three outcomes on fathers in periods *t0* and *t2* the results were robust. As the most important difference, the positive causal effect of paternal unemployment on daughters' years of worklessness about doubled in size and became

[15] The worklessness effects in rows one and two in **Table 4.1** for daughters increase from 0.08 to 0.11 and from 0.217 to 0.274 once the causal effects for single children are controlled.

statistically significant at the ten percent level. However, this does not change the nature of our conclusions and confirms the results of the fixed effects estimation (see **Table 4.2**).

In a separate test, we investigated whether the fixed effects results differ depending on the gender composition of the sibling pair. The results suggest that daughters' worklessness response to paternal unemployment is significantly stronger, if their older siblings are brothers rather than sisters. Among sons we find no difference in the worklessness but in the education effects of paternal unemployment: if the older sibling is female, sons tend to respond less negative to paternal unemployment than if the older sibling is male (results available upon request.) However, in most cases the gender of the older sibling did not modify the paternal unemployment effect in a statistically significant way.

We tested whether the results are sensitive to demanding a minimum age difference of 3 years for the considered sibling pairs in the fixed effects approach. This reduced the sample size by 35 percent but did not change our findings. Only the positive causal effects on daughters' education outcomes declined in magnitude and lost statistical significance (results available upon request).

Finally, we repeated the causal effects analyses for different treatment ages, as discussed in **Table 3**. **Table 5** shows the results for the Gottschalk and fixed effects approaches. The results for sons confirm that there is little evidence of causal paternal unemployment effects on son outcomes. Across both estimation approaches most of the estimates for sons are not statistically significantly different from zero. Whereas **Table 3** showed stronger correlation patterns if paternal unemployment occurred at a later age of sons this is not confirmed in the causal analyses; similarly, the correlation patterns for daughters in **Table 3** which show stronger correlations at younger treatment ages are not confirmed. The absence of treatment age patterns in the causal analysis suggests that the OLS patterns are driven by unobservables causing different biases at different treatment ages. For daughters we continue to find mostly positive effects of paternal unemployment on worklessness, however the effects are mostly statistically insignificant. Whereas the Gottschalk method generates significantly positive causal education effects for all treatment ages the fixed effects approach does not provide strong confirmation of these findings.

7 Explaining the gender differences

One of the most surprising findings of the analyses for youth experiencing paternal unemployment at age 10-15 is that the causal effect of paternal unemployment on daughters' educational attainment is positive. Although prior studies typically looked at short-term effects, only (e.g., Pinger 2012), our results stand in some contrast to them and this demands an explanation. An interpretation based on studies of gender-specific father-child interaction (e.g., Mammen 2011, Lundberg 2005) may be that fathers support their daughters only when they have additional leisure, e.g., after an unemployment shock. This shock may not be required for fathers to interact with sons. In this situation, daughters' education benefits from the additional attention but sons' education does not respond. While the patterns in the data match this explanation we have no additional evidence to support this potential mechanism. Instead, we study three further explanations that work through risk aversion, marriage market, and the maternal role model, respectively.

7.1 Risk aversion

It is well known that females are more risk averse than males (e.g., Borghans et al. 2009). If children perceive the family unemployment experience as a threat to their wellbeing, then risk averse individuals may respond by seeking insurance while risk neutral individuals may not. If education is considered as an insurance against income and unemployment risks, the typically more risk averse daughters may respond more strongly and pursue additional education after experiencing paternal unemployment.

In order to test the plausibility of this explanation we can use self-reported risk aversion information that is available in the SOEP data, compare it between males and females, and test whether more and less risk averse individuals respond differently to the experience of paternal unemployment.[16] On a scale from 0 (risk averse) to 10 (risk loving) the sample of daughters averaged at 4.95 and the sample of sons at 5.64, which confirms the general gender differences. In **Table 6** we show the results of the fixed effects estimation when we split the sample for the risk averse and the risk loving subsamples, where we grouped the sibling pairs by the risk aversion of the younger child. The evidence does not yield unambiguous support for our hypothesis. However, in three out of four education outcomes for daughters the paternal unemployment effect is either more statistically significant or larger for risk averse than for risk loving daughters: particularly upper secondary school and vocational training degrees (as reflected in the years of education measure) are certificates with reliable returns and signal value in the German labor market and here we observe larger responses among the risk averse. If investment in college education itself is a risky investment the resulting pattern of higher education effects among the risk loving is not surprising for this outcome. For sons the patterns in the education effect by risk aversion are less clear. While the evidence in **Table 6** is weak at best, risk aversion is a potential channel to explain the significantly positive education effect of daughters.[17]

7.2 Marriage market

A separate channel to explain daughters' positive education response to paternal unemployment might work through the marriage market. If daughters perceive a connection between individual unemployment risk and education, the experience of seeing their fathers unemployed may

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[16] Dohmen et al. (2011) compare alternative measures of risk aversion and find that the self-reported risk attitude is the best predictor of risk related behavioral choices.

[17] The patterns did not change when we controlled for the level of risk aversion, or grouped the subgroups by the risk aversion of the sibling-pairs instead of the younger, treated child.

motivate them to seek qualifications for a marriage market where they find a partner with a lower unemployment risk. Therefore, daughters may invest in additional education, whereas this mechanism is not relevant for sons.

To test this mechanism we compare the response of daughters of high and low educated fathers. If daughters of highly educated fathers experience paternal unemployment it is less likely that they perceive a correlation to paternal education and change their marriage market behaviors. We expect smaller positive causal education effects for them compared to daughters of lower educated fathers if the marriage market explanation is relevant. **Table 7** shows the results. The patterns agree with the hypothesized marriage market scenario: the estimated effect of paternal unemployment on daughters' human capital investment is larger and more statistically significant for daughters of fathers with lower education. In fact, the positive education effect of paternal unemployment appears to originate largely in the response of daughters of parents with lower educational background.

7.3 Reflecting maternal added worker effect

A third and final mechanism that may be behind the heterogeneity in male and female education responses to paternal unemployment may be related to the impact of the role model of mothers. If mothers respond to paternal unemployment by taking up employment or by increasing the number of hours worked, this might enhance their daughters' labor market orientation more than their sons' because the mother is a role model for girls. If own labor force participation seems more likely, the relevance of human capital investments increases and daughters may end up investing more in an education (for a discussion of such mechanisms see e.g. Goldin et al. 2006).

We test the plausibility of this scenario by separately estimating fixed effects models for children (i.e., sibling pairs) of mothers who were mostly employed vs. not employed when the children were aged 10-15. **Table 8** presents the estimation results. The results are mixed and do not unambiguously match the role model story which would suggest larger effects among daughters of employed mothers. Therefore we do not find strong support for the role model mechanism.[18]

8 Conclusions

In one of the first studies that looks at the longer term impact of paternal unemployment on child outcomes we separately evaluate correlations and causal effects for sons and daughters using rich and long running German household data. We find that past paternal unemployment correlates with higher worklessness and lower education of their children. We find these correlation patterns for paternal unemployment experiences regardless of treatment age at which children experienced paternal unemployment. When we apply the Gottschalk and the fixed effects methods to identify causal effects we find no effects of paternal unemployment on sons' outcomes. This is in line with the international literature. The situation looks different for daughters. For daughters, who are studied less often in the international literature, we find evidence of positive intergenerational transmission of unemployment, i.e., daughters are workless more in response to experiencing paternal unemployment. A surprising finding is that daughters of previously unemployed fathers increase their educational attainment compared to daughters of fathers who did not experience unemployment. Thus, paternal unemployment causes daughters to spend more time in education and in worklessness as opposed to work when they are aged 17-24.

A number of robustness tests confirm these results. The implication for sons is that there is no reason to address fathers in order to either reduce sons' worklessness or to increase their education. In contrast, our evidence suggests that daughters' worklessness may decline if the labor market conditions improve for their fathers. We propose three mechanisms that might

[18] The patterns did not change when we controlled for maternal employment during childhood in the empirical model.

drive the surprising positive causal effect of paternal unemployment on daughters' education. The evidence is weak at best regarding the relevance of risk aversion, however, we cannot exclude the possibility that daughters invest more in their education as an insurance device after experiencing a paternal unemployment shock. We find support for the hypothesis that marriage market considerations are behind the positive response of daughters' education to paternal unemployment; possibly daughters of fathers with low education attempt to improve their marriage market prospects by attaining additional education in response to experiencing paternal unemployment. We find no clear support for a maternal role model mechanism.

Overall, our results show that gender differences exist. As this may be connected to conservative gender role models still prevalent in the German society it is of interest to research gender differences in intergenerational transmission in more egalitarian societies.

References

Ananat, E.O., A. Gassman-Pines, C.M. Gibson-Davis (2008), The Effects of Plant Closings on Children's Educational Achievement. Working Paper. Duke University.

Andersen, S.H. (2013), Common Genes or Exogenous Shock? Disentangling the Causal Effect of Paternal Unemployment on Children's Schooling Efforts, European Sociological Review 29(3): 477-488.

Antel, J.J. (1992), The intergenerational transfer of welfare dependency: Some statistical evidence. The Review of Economics and Statistics, 74: 467-473.

Borghans, L., J.J. Heckman, B.H.H. Golsteyn, H. Meijers (2005), Gender differences in risk aversion and ambiguity aversion, Journal of the European Economic Association 7(2-3): 649-658.

Cameron, S.V., C. Taber (2004), Estimation of Educational Borrowing Constraints Using Returns to Schooling, Journal of Political Economy 112: 132-182.

Card, D. (1999), The causal effect of education on earnings. in: O. Ashenfelter, D. Card (eds.) Handbook of Labor Economics, volume 3B, North Holland, Amsterdam et al.: 1801-1863.

Coelli, M.B. (2011), Parental job loss and the education enrollment of youth, Labour Economics 18: 25-35.

Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, G.G. Wagner (2011), Individual risk attitudes: measurement, determinants, and behavioral consequences, Journal of the European Economic Association 9(3): 522-550.

Edmark, K., K. Hanspers (2012), Is welfare dependency inherited? Estimating the causal welfare transmission effects using Swedish sibling data. IFN Working Paper No. 894, Stockholm.

Ekhaugen, T. (2009), Extracting the causal component from the intergenerational correlation in unemployment. Journal of Population Economics 22: 97-113.

Goldin, Claudia, Lawrence F. Katz, and Ilyana Kuziemko. (2006), The Homecoming of American College Women: The Reversal of the College Gender Gap, Journal of Economic Perspectives 20(4), 133-156.

Gottschalk, P. (1996), Is the correlation in welfare participation across generations spurious? Journal of Public Economics 63: 1-25.

Gregg, P. (2001), The impact of youth unemployment on adult unemployment in the NCDS. Economic Journal 111: F626-F653.

Gregg, P., L. Macmillan, B. Nasim (2012), The impact of fathers' job loss during the recession of the 1980s on their children's educational attainment and labour market outcomes. Fiscal Studies 33: 237-264.

Johnson, P., H. Reed (1996), Intergenerational mobility among the rich and poor: results from the National Child Development Survey. Oxford Review of Economic Policy 12: 127-42.

Lundberg, S. (2005), Sons, daughters, and parental behavior, Oxford Review of Economic Policy 21: 340-356.

Macmillan, L. (2010), The Intergenerational Transmission of Worklessness in the UK. CMPO Working Paper Series No. 10/231. Bristol.

Macmillan, L. (2014), Intergenerational worklessness in the UK and the role of local labour markets. Oxford Economic Papers, doi:10.1093/oep/gpt046

Maeder, M., S. Müller, R.T. Riphahn, and C. Schwientek, 2014, Intergenerational transmission of unemployment - evidence for German sons, IZA Discussion Paper No. 8513, IZA Bonn, forthcoming: Journal of Economics and Statistics (Jahrbücher für Nationalökonomie und Statistik).

Mammen, K. (2011), Fathers' time investment in children: do sons get more?, Journal of Population Economics 24:839-871.
OECD (2012), Länderüberblick: Bildung auf einen Blick 2012: OECD Indikatoren 2012. Deutschland, www.oecd.org/education/country%20note%20Germany%20%28DE%29.pdf (last access: Jan 3, 2013).
OECD (2014), Education at a Glance: OECD Indicators, OECD Publishing, Paris.
O'Neill, D., O. Sweetman (1998), Intergenerational mobility in Britain: evidence from unemployment patterns. Oxford Bulletin of Economics and Statistics 60: 431-447.
Oreopoulos, P., M. Page, A. Huff Stevens (2008), The intergenerational effect of worker displacement. Journal of Labor Economics 26: 455-483.
Pinger, P.R. (2012), Intergenerational Effects of Economic Distress: Paternal Unemployment and Child Secondary Schooling Decisions. mimeo. University of Mannheim.
Rege, Mari, Kjetil Telle, and Mark Votruba, 2011, Parental Job Loss and Children's School Performance, Review of Economic Studies 78: 1462-1489.
Schmillen, A., M. Umkehrer (2013), The scars of youth. Effects of early-career unemployment on future unemployment experience, IAB Discussion Paper No. 6/2013, Nürnberg.
Stevens, D.H., J. Schaller (2011), Short-run effects of parental job loss on children's academic achievement, Economics of Education Review 30: 289-299.
Wagner, G.G., J.R. Frick, J. Schupp (2007), The German Socio-Economic Panel Study (SOEP) - Scope, Evolution and Enhancements. Schmollers Jahrbuch (Journal of Applied Social Science Studies) 127: 139-169.
Wightman, P. (2012), Parental Job Loss, Parental Ability and Children’s Educational Attainment. Research Report 12-761. Ann Arbor: Population Studies Center, University of Michigan.

Table 1 Descriptive statistics on dependent variables

		Sons			Daughters		
		All	Father unempl. in t0		All	Father unempl. in t0	
			no	yes		no	yes
Ever workless (0/1)	Mean	0,221	0,205	0,366	0,222	0,206	0,348
	St.Dev.	(0.415)	(0.404)	(0.483)	(0.416)	(0.405)	(0.477)
	N	2202	1978	224	2106	1876	230
Years workless	Mean	0,338	0,300	0,679	0,357	0,317	0,687
	St.Dev.	(0.776)	(0.716)	(1.126)	(0.837)	(0.761)	(1.256)
	N	2202	1978	224	2106	1876	230
Any upper sec. school (0/1)	Mean	0,443	0,462	0,272	0,501	0,513	0,399
	St.Dev.	(0.497)	(0.499)	(0.446)	(0.500)	(0.500)	(0.491)
	N	2093	1880	213	1998	1775	223
Upper sec. sch. degree (0/1)	Mean	0,419	0,441	0,220	0,479	0,493	0,361
	St.Dev.	(0.494)	(0.497)	(0.416)	(0.500)	(0.500)	(0.482)
	N	1254	1127	127	1224	1091	133
Any college (0/1)	Mean	0,302	0,325	0,123	0,321	0,339	0,178
	St.Dev.	(0.459)	(0.468)	(0.330)	(0.467)	(0.474)	(0.383)
	N	1402	1248	154	1347	1195	152
Years education at 22	Mean	11.490	11.545	10.981	11.732	11.777	11.382
	St.Dev.	(1.605)	(1.615)	(1.419)	(1.686)	(1.665)	(1.811)
	N	1064	960	104	1039	920	119

Note: The descriptive statistics describe the dependent variables as they are used in the correlation analyses. For the causal studies samples are reduced to either consider older siblings or observations on paternal unemployment at an older age.
Source: SOEP (1984-2012).

Table 2 Coefficient estimates on paternal unemployment in linear regression models

	Sons		Daughters	
	basic	extended	basic	extended
Ever workless (0/1)	0.153 ***	0.046	0.135 ***	0.051
	(0.035)	(0.035)	(0.033)	(0.036)
Years workless	0.367 ***	0.176 **	0.356 ***	0.163 *
	(0.079)	(0.074)	(0.085)	(0.084)
Any upper sec. school (0/1)	-0.193 ***	-0.028	-0.126 ***	0.020
	(0.033)	(0.037)	(0.038)	(0.037)
Upper sec. school degree (0/1)	-0.219 ***	-0.084 *	-0.136 ***	-0.019
	(0.041)	(0.045)	(0.046)	(0.045)
Any college (0/1)	-0.184 ***	-0.058 *	-0.176 ***	-0.058
	(0.031)	(0.035)	(0.036)	(0.038)
Years education at 22	-0.618 ***	-0.212	-0.414 **	-0.136
	(0.147)	(0.155)	(0.177)	(0.177)

Note: Each entry reflects the coefficient on paternal unemployment taken from a separate regression. The left column describes the dependent variable. The basic specification controls for missing value indicators, the extended specification considers all controls as described in section 4.3. Standard errors are clustered at the level of fathers; * p<0.1, ** p<0.05, *** p<0.01.

Source: SOEP (1984-2012).

Table 3 Impact of treatment age on correlation patterns

	Sons			Daughters		
Treatment age:	8-13	10-15	12-17	8-13	10-15	12-17
Ever workless (0/1)	0.032	0.046	0.045	0.022	0.051	0.032
	(0.037)	(0.035)	(0.034)	(0.038)	(0.036)	(0.032)
Years workless	0.109	0.176 **	0.192 **	0.222 **	0.163 *	0.077
	(0.077)	(0.074)	(0.077)	(0.100)	(0.084)	(0.077)
Any upper sec. school (0/1)	0.034	-0.028	-0.068 *	-0.023	0.020	0.005
	(0.043)	(0.037)	(0.035)	(0.042)	(0.037)	(0.036)
Upper sec. school degree (0/1)	0.053	-0.084 *	-0.107 **	-0.099 *	-0.019	-0.055
	(0.058)	(0.045)	(0.043)	(0.054)	(0.045)	(0.045)
Any college (0/1)	-0.045	-0.058 *	-0.054	-0.089 *	-0.058	-0.059
	(0.042)	(0.035)	(0.034)	(0.046)	(0.038)	(0.038)
Years education at 22	-0.093	-0.212	-0.288 *	-0.614 ***	-0.136	-0.102
	(0.178)	(0.155)	(0.155)	(0.228)	(0.177)	(0.182)

Note: The estimations use the extended specification, see Table 2. The number of observations varies across entries. We use 1845 / 2202 / 2465 observations for the three age groups for sons and 1735/ 2106 / 2367 for daughters for the worklessness outcomes. All estimations apply the extended specification of the regression model; * p<0.1, ** p<0.05, *** p<0.01.

Source: SOEP (1984-2012).

Table 4 Estimation of causal effects

4.1 Gottschalk method

	Sons	Daughters
Ever workless (0/1)	-0.042	0.080
	(0.081)	(0.081)
Years workless	-0.111	0.217
	(0.151)	(0.194)
Any upper sec. school (0/1)	-0.137 *	-0.080
	(0.071)	(0.065)
Upper sec. school degree (0/1)	-0.148 *	0.176 **
	(0.084)	(0.074)
Any college (0/1)	-0.006	0.142 **
	(0.083)	(0.072)
Years education at 22	-0.042	0.707 ***
	(0.333)	(0.267)

4.2 Sibling fixed effects

	Sons	Daughters
Ever workless (0/1)	0.049	0.126
	(0.106)	(0.102)
Years workless	0.156	0.418 *
	(0.192)	(0.229)
Any upper sec. school (0/1)	0.105	0.096
	(0.091)	(0.099)
Upper sec. school degree (0/1)	0.023	0.333 ***
	(0.145)	(0.123)
Any college (0/1)	-0.086	0.184 *
	(0.104)	(0.100)
Years education at 22	0.031	0.540 *
	(0.404)	(0.323)

Note: The estimations in Table 4.1 use the extended specification (Table 2). The number of observations varies across entries. In Table 4.1 we use 906 and 908 observations for worklessness outcomes for sons and daughters, respectively. In Table 4.2 we control for child year of birth, birth order, and the state by cohort specific cohort share of upper secondary school degree holders in addition to missing value indicators for father observations in *t0* (6 indicators for age 10-15) and for child observations in *t1* (8 indicators for age 17-14). Here, we use 1860 and 1788 observations for worklessness outcomes for sons and daughters, respectively; * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Source: SOEP (1984-2012).

Table 5 Estimation of causal effects by treatment age

5.1 Gottschalk method

	Sons			Daughters		
Treatment age:	8-13	10-15	12-17	8-13	10-15	12-17
Ever workless (0/1)	0.001	-0.042	-0.049	0.032	0.080	0.044
	(0.101)	(0.081)	(0.079)	(0.092)	(0.081)	(0.076)
Years workless	-0.090	-0.111	0.007	0.442 *	0.217	0.147
	(0.188)	(0.151)	(0.153)	(0.248)	(0.194)	(0.187)
Any upper sec. school (0/1)	-0.101	-0.137 *	-0.126 *	-0.083	-0.080	-0.100
	(0.088)	(0.071)	(0.070)	(0.087)	(0.065)	(0.069)
Upper sec. school degree (0/1)	0.051	-0.148 *	-0.169 **	0.128	0.176 **	0.150 *
	(0.110)	(0.084)	(0.080)	(0.098)	(0.074)	(0.078)
Any college (0/1)	0.099	-0.006	-0.062	0.120	0.142 **	0.083
	(0.101)	(0.083)	(0.073)	(0.083)	(0.072)	(0.071)
Years education at 22	0.022	-0.042	-0.127	0.346	0.707 ***	0.681 **
	(0.420)	(0.333)	(0.299)	(0.356)	(0.267)	(0.290)

5.2 Sibling fixed effects

	Sons			Daughters		
Treatment age:	8-13	10-15	12-17	8-13	10-15	12-17
Ever workless (0/1)	0.113	0.049	-0.057	-0.055	0.126	0.020
	(0.118)	(0.106)	(0.090)	(0.106)	(0.102)	(0.079)
Years workless	0.338	0.156	-0.035	0.032	0.418 *	-0.073
	(0.236)	(0.192)	(0.158)	(0.249)	(0.229)	(0.189)
Any upper sec. school (0/1)	0.107	0.105	-0.005	0.131	0.096	-0.060
	(0.097)	(0.091)	(0.065)	(0.118)	(0.099)	(0.078)
Upper sec. school degree (0/1)	0.088	0.023	0.080	0.040	0.333 ***	-0.126
	(0.178)	(0.145)	(0.128)	(0.259)	(0.123)	(0.107)
Any college (0/1)	-0.107	-0.086	-0.091	0.067	0.184 *	-0.082
	(0.107)	(0.104)	(0.102)	(0.122)	(0.100)	(0.064)
Years education at 22	0.490	0.031	0.098	-0.526	0.540 *	0.614
	(0.366)	(0.404)	(0.418)	(0.701)	(0.323)	(0.378)

Note: The estimations in Table 5.1 use the extended specification (Table 2). The number of observations varies across entries. In Table 5.1 we use 682 / 1034 and 686 / 1053 observations for worklessness outcomes for ages 8-13 / 12-17 for sons and daughters, respectively. Estimates for age groups 10-15 are from Table 4. The specifications in Table 8.2 are as in Table 4.2 except for adjusted missing value indicators. Here, we use 1454 / 2169 and 1468 / 2076 observations for worklessness outcomes for ages 8-13 / 12-17 for sons and daughters, respectively; the education outcomes use substantially fewer observations; * p<0.1, ** p<0.05, *** p<0.01.
Source: SOEP (1984-2012).

Table 6 Estimation results: sibling fixed effects by subjective risk aversion

	Sons		Daughters	
	risk averse	risk loving	risk averse	risk loving
Any upper sec. school (0/1)	0.168 *	0.084	0.243 *	0.258
	(0.096)	(0.137)	(0.143)	(0.168)
Upper sec. school degree (0/1)	0.040	0.404	0.366 *	0.341
	(0.179)	(0.287)	(0.214)	(0.233)
Any college (0/1)	-0.096	-0.080	0.031	0.457 ***
	(0.182)	(0.146)	(0.181)	(0.167)
Years education at 22	0.793	-0.181	0.623	0.087
	(0.560)	(0.697)	(0.405)	(0.389)

Note: The risk aversion indicator is available only for the survey years 2004, 2006, 2008-2012; therefore the estimates are based partly on no more than 220 observations in the gender by risk aversion type groups. We control for the extended set of controls as in Table 4.2. For the first outcome we use 446 and 702 individual observations for sons and 522 and 650 individual observations for daughters by subjective risk aversion status, respectively.
* p<0.1, ** p<0.05, *** p<0.01.
Source: SOEP (1984-2012).

Table 7 Estimation results: sibling fixed effects by paternal education level for daughters

Daughters	Paternal level of education high	low
Any upper sec. school (0/1)	0.054	0.075
	(0.211)	(0.109)
Upper sec.school degree (0/1)	0.183	0.333 **
	(0.236)	(0.140)
Any college (0/1)	0.059	0.198 **
	(0.412)	(0.093)
Years of education at age 22	-0.508	0.902 *
	(0.814)	(0.469)

Note: Paternal education is coded high if fathers hold an upper secondary school degree and low otherwise. Up to thirty percent of the observations have fathers with high education in this definition. We control for the extended set of controls as in Table 4.2 and use a total of 1.630 observations for the outcome any upper secondary school (414 with high and 1216 with low educated fathers); * p<0.1, ** p<0.05, *** p<0.01.
Source: SOEP (1984-2012).

Table 8 Estimation results: sibling fixed effects by maternal labor force participation

	Sons		Daughters	
	mother mostly employed	mother mostly not employed	mother mostly employed	mother mostly not employed
Any upper sec. school (0/1)	0.152	0.115	0.025	0.206 *
	(0.149)	(0.110)	(0.175)	(0.123)
Upper sec. school degree (0/1)	0.253	-0.140	0.313	0.247 *
	(0.226)	(0.174)	(0.193)	(0.146)
Any college (0/1)	-0.070	-0.113	0.528 ***	-0.026
	(0.178)	(0.163)	(0.172)	(0.166)
Years education at 22	0.294	1.218 **	0.712	0.746 *
	(0.792)	(0.476)	(0.688)	(0.429)

Note: Mothers are considered to be mostly employed if they indicated in at least half of the surveys during the younger child's childhood (age 10-15) to be in part-time or full-time employment. We control for the extended set of controls as in Table 4.2. For the first outcome we use 872 and 582 individual observations for sons and 734 and 644 individual observations for daughters by maternal employment status, respectively. In part, the estimates are based on no more than 200 observations in the gender by maternal employment groups; * p<0.1, ** p<0.05, *** p<0.01.
Source: SOEP (1984-2012).

Appendix Descriptive statistics on all explanatory variables

		Sons			Daughters		
		All	Father unempl. in t0		All	Father unempl. in t0	
			no	yes		no	yes
Father ever unemployed 1/0	Mean	0,102	0,000	1.000	0,109	0,000	1.000
	Std.Dev.	(0.302)	(0.000)	(0.000)	(0.312)	(0.000)	(0.000)
Info Father missing when child 10	Mean	0,409	0,424	0,272	0,413	0,430	0,278
	Std.Dev.	(0.492)	(0.494)	(0.446)	(0.493)	(0.495)	(0.449)
Info Father missing when child 11	Mean	0,346	0,363	0,192	0,361	0,382	0,196
	Std.Dev.	(0.476)	(0.481)	(0.395)	(0.481)	(0.486)	(0.398)
Info Father missing when child 12	Mean	0,266	0,278	0,161	0,287	0,303	0,161
	Std.Dev.	(0.442)	(0.448)	(0.368)	(0.453)	(0.460)	(0.368)
Info Father missing when child 13	Mean	0,195	0,208	0,080	0,206	0,214	0,135
	Std.Dev.	(0.397)	(0.406)	(0.272)	(0.404)	(0.410)	(0.342)
Info Father missing when child 14	Mean	0,121	0,126	0,080	0,134	0,137	0,109
	Std.Dev.	(0.326)	(0.332)	(0.272)	(0.341)	(0.344)	(0.312)
Info Father missing when child 15	Mean	0,029	0,029	0,022	0,045	0,044	0,052
	Std.Dev.	(0.167)	(0.169)	(0.148)	(0.207)	(0.205)	(0.223)
Info Child missing age 17	Mean	0,046	0,046	0,049	0,047	0,048	0,035
	Std.Dev.	(0.209)	(0.208)	(0.217)	(0.211)	(0.214)	(0.184)
Info Child missing age 18	Mean	0,118	0,121	0,089	0,123	0,127	0,091
	Std.Dev.	(0.323)	(0.327)	(0.286)	(0.329)	(0.334)	(0.289)
Info Child missing age 19	Mean	0,206	0,207	0,196	0,211	0,218	0,157
	Std.Dev.	(0.405)	(0.405)	(0.398)	(0.408)	(0.413)	(0.364)
Info Child missing age 20	Mean	0,290	0,294	0,254	0,305	0,307	0,291
	Std.Dev.	(0.454)	(0.456)	(0.437)	(0.461)	(0.461)	(0.455)
Info Child missing age 21	Mean	0,389	0,395	0,330	0,384	0,386	0,370
	Std.Dev.	(0.488)	(0.489)	(0.471)	(0.487)	(0.487)	(0.484)
Info Child missing age 22	Mean	0,460	0,463	0,438	0,454	0,459	0,413
	Std.Dev.	(0.499)	(0.499)	(0.497)	(0.498)	(0.498)	(0.493)
Info Child missing age 23	Mean	0,549	0,548	0,554	0,526	0,527	0,513
	Std.Dev.	(0.498)	(0.498)	(0.498)	(0.499)	(0.499)	(0.501)
Info Child missing age 24	Mean	0,607	0,603	0,643	0,591	0,593	0,570
	Std.Dev.	(0.489)	(0.489)	(0.480)	(0.492)	(0.491)	(0.496)
Max. number of observation periods	Mean	6.980	6.965	7.116	7.000	6.989	7.087
	Std.Dev.	(1.888)	(1.912)	(1.661)	(1.924)	(1.948)	(1.718)
Child year of birth	Mean	1983.3	1983.3	1984.1	1983.1	1983.0	1984.1
	Std.Dev.	(7.305)	(7.421)	(6.153)	(7.375)	(7.497)	(6.225)
Child number of siblings	Mean	1.568	1.549	1.732	1.618	1.574	1.983
	Std.Dev.	(1.190)	(1.180)	(1.270)	(1.244)	(1.199)	(1.515)
1st born	Mean	0,353	0,358	0,313	0,353	0,353	0,348
	Std.Dev.	(0.478)	(0.480)	(0.465)	(0.478)	(0.478)	(0.477)
2nd born	Mean	0,361	0,365	0,326	0,361	0,365	0,326
	Std.Dev.	(0.480)	(0.481)	(0.470)	(0.480)	(0.482)	(0.470)
3rd born	Mean	0,104	0,101	0,138	0,101	0,101	0,104
	Std.Dev.	(0.306)	(0.301)	(0.346)	(0.302)	(0.301)	(0.306)
4th born and higher	Mean	0,032	0,031	0,045	0,036	0,034	0,052
	Std.Dev.	(0.177)	(0.173)	(0.207)	(0.185)	(0.180)	(0.223)
Missing information	Mean	0,149	0,146	0,179	0,150	0,147	0,170
	Std.Dev.	(0.357)	(0.353)	(0.384)	(0.357)	(0.354)	(0.376)
Child state Kind Schleswig H. + Hamburg	Mean	0,041	0,043	0,018	0,047	0,047	0,039
	Std.Dev.	(0.198)	(0.204)	(0.133)	(0.211)	(0.213)	(0.194)
Child state Niedersachsen + Bremen	Mean	0,084	0,086	0,063	0,09	0,093	0,070
	Std.Dev.	(0.277)	(0.281)	(0.243)	(0.287)	(0.290)	(0.255)
Child state NRW	Mean	0,190	0,190	0,192	0,208	0,216	0,139
	Std.Dev.	(0.392)	(0.392)	(0.395)	(0.406)	(0.412)	(0.347)
Child state Hessen	Mean	0,065	0,070	0,027	0,054	0,058	0,022
	Std.Dev.	(0.247)	(0.255)	(0.162)	(0.225)	(0.233)	(0.146)
Child state Rheinland Pfalz + Saarland	Mean	0,059	0,061	0,045	0,055	0,057	0,035
	Std.Dev.	(0.236)	(0.239)	(0.207)	(0.227)	(0.232)	(0.184)
Child state Baden Württemberg	Mean	0,112	0,119	0,054	0,105	0,113	0,039
	Std.Dev.	(0.316)	(0.324)	(0.226)	(0.307)	(0.317)	(0.194)
Child state Bayern	Mean	0,140	0,149	0,067	0,150	0,159	0,070
	Std.Dev.	(0.347)	(0.356)	(0.251)	(0.357)	(0.366)	(0.255)
Child state Berlin	Mean	0,032	0,030	0,049	0,032	0,030	0,048
	Std.Dev.	(0.177)	(0.172)	(0.217)	(0.176)	(0.170)	(0.214)
Child state Brandenburg	Mean	0,051	0,047	0,094	0,047	0,041	0,096
	Std.Dev.	(0.221)	(0.211)	(0.292)	(0.211)	(0.197)	(0.295)
Child state Mecklenburg Vorpommern	Mean	0,032	0,028	0,067	0,030	0,026	0,070
	Std.Dev.	(0.177)	(0.166)	(0.251)	(0.172)	(0.158)	(0.255)
Child state Sachsen	Mean	0,088	0,082	0,138	0,080	0,075	0,122
	Std.Dev.	(0.284)	(0.275)	(0.346)	(0.272)	(0.264)	(0.328)
Child state Sachsen-Anhalt	Mean	0,052	0,050	0,071	0,056	0,045	0,148
	Std.Dev.	(0.222)	(0.217)	(0.258)	(0.230)	(0.207)	(0.356)
Child state Thüringen	Mean	0,053	0,046	0,116	0,048	0,041	0,104
	Std.Dev.	(0.223)	(0.208)	(0.321)	(0.214)	(0.198)	(0.306)

Interview Month January	Mean	0,110	0,101	0,192	0,104	0,098	0,157
	Std.Dev.	(0.313)	(0.301)	(0.395)	(0.306)	(0.298)	(0.364)
Interview Month February	Mean	0,208	0,205	0,228	0,212	0,201	0,300
	Std.Dev.	(0.406)	(0.404)	(0.420)	(0.409)	(0.401)	(0.459)
Interview Month March	Mean	0,241	0,249	0,165	0,245	0,257	0,152
	Std.Dev.	(0.428)	(0.433)	(0.372)	(0.430)	(0.437)	(0.360)
Interview Month April	Mean	0,073	0,075	0,054	0,072	0,074	0,057
	Std.Dev.	(0.260)	(0.263)	(0.226)	(0.259)	(0.262)	(0.231)
Interview Month May	Mean	0,033	0,034	0,022	0,038	0,039	0,026
	Std.Dev.	(0.179)	(0.182)	(0.148)	(0.191)	(0.195)	(0.160)
Interview Month June	Mean	0,019	0,019	0,022	0,022	0,023	0,009
	Std.Dev.	(0.137)	(0.136)	(0.148)	(0.146)	(0.151)	(0.093)
Interview Month July	Mean	0,015	0,015	0,018	0,013	0,013	0,009
	Std.Dev.	(0.123)	(0.122)	(0.133)	(0.113)	(0.115)	(0.093)
Interview Month August-December	Mean	0,013	0,014	0,004	0,015	0,015	0,009
	Std.Dev.	(0.112)	(0.116)	(0.067)	(0.120)	(0.123)	(0.093)
Interview Month Missing	Mean	0,289	0,288	0,295	0,278	0,278	0,283
	Std.Dev.	(0.453)	(0.453)	(0.457)	(0.448)	(0.448)	(0.451)
Number of individuals in household	Mean	4.064	4.080	3.920	4.078	4.093	3.952
	Std.Dev.	(1.054)	(1.043)	(1.138)	(1.118)	(1.097)	(1.279)
State cohort share with upper sec. degree	Mean	0,381	0,382	0,375	0,442	0,442	0,446
	Std.Dev.	(0.066)	(0.065)	(0.075)	(0.076)	(0.076)	(0.074)
Father-No postsecondary education	Mean	0,059	0,050	0,147	0,071	0,068	0,091
	Std.Dev.	(0.237)	(0.217)	(0.355)	(0.256)	(0.252)	(0.289)
Father-Other vocational training	Mean	0,061	0,056	0,107	0,076	0,068	0,148
	Std.Dev.	(0.239)	(0.229)	(0.310)	(0.266)	(0.251)	(0.356)
Father-Industrial/commercial/health care apprenticeship	Mean	0,497	0,484	0,612	0,483	0,467	0,613
	Std.Dev.	(0.500)	(0.500)	(0.488)	(0.500)	(0.499)	(0.488)
Father-Technical college, civil servant training	Mean	0,151	0,161	0,063	0,136	0,143	0,078
	Std.Dev.	(0.358)	(0.367)	(0.243)	(0.343)	(0.351)	(0.269)
Father-University degree	Mean	0,232	0,250	0,071	0,234	0,254	0,070
	Std.Dev.	(0.422)	(0.433)	(0.258)	(0.423)	(0.435)	(0.255)
Mother-No postsecondary education	Mean	0,144	0,138	0,201	0,158	0,151	0,217
	Std.Dev.	(0.351)	(0.344)	(0.402)	(0.365)	(0.358)	(0.413)
Mother-Other vocational training	Mean	0,05	0,051	0,045	0,052	0,052	0,048
	Std.Dev.	(0.219)	(0.220)	(0.207)	(0.222)	(0.223)	(0.214)
Mother-Industrial/commercial/health care apprenticeship	Mean	0,573	0,569	0,607	0,564	0,565	0,557
	Std.Dev.	(0.495)	(0.495)	(0.489)	(0.496)	(0.496)	(0.498)
Mother-Technical college, civil servant training	Mean	0,057	0,058	0,049	0,053	0,055	0,030
	Std.Dev.	(0.231)	(0.233)	(0.217)	(0.224)	(0.229)	(0.172)
Mother-University degree	Mean	0,176	0,185	0,098	0,173	0,176	0,148
	Std.Dev.	(0.381)	(0.388)	(0.298)	(0.379)	(0.381)	(0.356)
Father-Lower secondary school degree (Hauptschule)	Mean	0,023	0,018	0,067	0,021	0,017	0,057
	Std.Dev.	(0.149)	(0.132)	(0.251)	(0.143)	(0.128)	(0.231)
Father-Intermediate school degree (Mittlere Reife)	Mean	0,392	0,384	0,469	0,406	0,399	0,457
	Std.Dev.	(0.488)	(0.486)	(0.500)	(0.491)	(0.490)	(0.499)
Father-Technical school degree (Fachhochschulreife)	Mean	0,346	0,342	0,379	0,325	0,319	0,374
	Std.Dev.	(0.476)	(0.474)	(0.486)	(0.468)	(0.466)	(0.485)
Father-Upper secondary school degree (Abitur)	Mean	0,239	0,257	0,085	0,249	0,265	0,113
	Std.Dev.	(0.427)	(0.437)	(0.279)	(0.432)	(0.442)	(0.317)
Mother-Lower secondary school degree (Hauptschule)	Mean	0,038	0,034	0,071	0,038	0,036	0,061
	Std.Dev.	(0.190)	(0.181)	(0.258)	(0.192)	(0.186)	(0.240)
Mother-Intermediate school degree (Mittlere Reife)	Mean	0,331	0,328	0,357	0,358	0,359	0,343
	Std.Dev.	(0.471)	(0.470)	(0.480)	(0.479)	(0.480)	(0.476)
Mother-Technical school degree (Fachhochschulreife)	Mean	0,457	0,452	0,504	0,422	0,410	0,517
	Std.Dev.	(0.498)	(0.498)	(0.501)	(0.494)	(0.492)	(0.501)
Mother-Upper secondary school degree (Abitur)	Mean	0,174	0,186	0,067	0,182	0,195	0,078
	Std.Dev.	(0.379)	(0.389)	(0.251)	(0.386)	(0.396)	(0.269)
Father Civil Servant	Mean	0,103	0,113	0,013	0,102	0,113	0,013
	Std.Dev.	(0.304)	(0.316)	(0.115)	(0.303)	(0.317)	(0.114)
Father White Collar	Mean	0,352	0,373	0,170	0,338	0,359	0,165
	Std.Dev.	(0.478)	(0.484)	(0.376)	(0.473)	(0.480)	(0.372)
Father Self-Employed	Mean	0,129	0,131	0,107	0,134	0,142	0,070
	Std.Dev.	(0.335)	(0.337)	(0.310)	(0.341)	(0.349)	(0.255)
Father Blue Collar	Mean	0,346	0,341	0,388	0,351	0,341	0,435
	Std.Dev.	(0.476)	(0.474)	(0.488)	(0.477)	(0.474)	(0.497)
Father Other	Mean	0,07	0,041	0,321	0,073	0,043	0,317
	Std.Dev.	(0.255)	(0.199)	(0.468)	(0.260)	(0.203)	(0.466)
Father Info Missing	Mean	0,001	0,001	0,000	0,002	0,002	0,000
	Std.Dev.	(0.030)	(0.032)	(0.000)	(0.044)	(0.046)	(0.000)
Mother Civil Servant	Mean	0,04	0,043	0,009	0,036	0,039	0,004
	Std.Dev.	(0.195)	(0.203)	(0.094)	(0.185)	(0.195)	(0.066)
Mother White Collar	Mean	0,26	0,271	0,165	0,252	0,264	0,152
	Std.Dev.	(0.439)	(0.445)	(0.372)	(0.434)	(0.441)	(0.360)
Mother Self-Employed	Mean	0,056	0,056	0,054	0,062	0,064	0,048
	Std.Dev.	(0.230)	(0.230)	(0.226)	(0.242)	(0.245)	(0.214)
Mother Blue Collar	Mean	0,119	0,114	0,170	0,105	0,104	0,117
	Std.Dev.	(0.324)	(0.318)	(0.376)	(0.307)	(0.305)	(0.323)
Mother Other	Mean	0,11	0,096	0,241	0,113	0,092	0,283
	Std.Dev.	(0.313)	(0.294)	(0.429)	(0.316)	(0.289)	(0.451)
Mother Info Missing	Mean	0,415	0,421	0,362	0,432	0,437	0,396
	Std.Dev.	(0.493)	(0.494)	(0.482)	(0.495)	(0.496)	(0.490)
Father year of birth	Mean	1953.4	1953.1	1955.6	1953.3	1953.1	1954.7
	Std.Dev.	(8.854)	(8.873)	(8.363)	(8.912)	(8.908)	(8.833)

Father state Schleswig H. + Hamburg	Mean	0,039	0,041	0,018	0,044	0,045	0,035
	Std.Dev.	(0.193)	(0.198)	(0.133)	(0.205)	(0.208)	(0.184)
Father state Niedersachsen + Bremen	Mean	0,084	0,086	0,063	0,089	0,092	0,061
	Std.Dev.	(0.277)	(0.281)	(0.243)	(0.285)	(0.289)	(0.240)
Father state NRW	Mean	0,189	0,19	0,183	0,208	0,216	0,143
	Std.Dev.	(0.392)	(0.392)	(0.388)	(0.406)	(0.412)	(0.351)
Father state Hessen	Mean	0,068	0,072	0,031	0,053	0,057	0,022
	Std.Dev.	(0.252)	(0.259)	(0.174)	(0.224)	(0.231)	(0.146)
Father state Rheinland Pfalz + Saarland	Mean	0,057	0,059	0,045	0,052	0,054	0,035
	Std.Dev.	(0.232)	(0.235)	(0.207)	(0.223)	(0.227)	(0.184)
Father state Baden Württemberg	Mean	0,114	0,121	0,049	0,103	0,111	0,035
	Std.Dev.	(0.318)	(0.327)	(0.217)	(0.304)	(0.315)	(0.184)
Father state Bayern	Mean	0,133	0,141	0,058	0,146	0,156	0,061
	Std.Dev.	(0.339)	(0.348)	(0.234)	(0.353)	(0.363)	(0.240)
Father state Berlin	Mean	0,037	0,035	0,058	0,034	0,031	0,057
	Std.Dev.	(0.189)	(0.184)	(0.234)	(0.182)	(0.175)	(0.231)
Father state Brandenburg	Mean	0,049	0,043	0,094	0,047	0,041	0,096
	Std.Dev.	(0.215)	(0.204)	(0.292)	(0.211)	(0.197)	(0.295)
Father state Mecklenburg Vorpommern	Mean	0,032	0,028	0,063	0,032	0,027	0,074
	Std.Dev.	(0.175)	(0.166)	(0.243)	(0.176)	(0.161)	(0.262)
Father state Sachsen	Mean	0,093	0,087	0,143	0,087	0,082	0,130
	Std.Dev.	(0.290)	(0.282)	(0.351)	(0.282)	(0.274)	(0.338)
Father state Sachsen-Anhalt	Mean	0,053	0,050	0,076	0,057	0,047	0,143
	Std.Dev.	(0.223)	(0.218)	(0.265)	(0.233)	(0.211)	(0.351)
Father state Thüringen	Mean	0,053	0,046	0,121	0,048	0,041	0,109
	Std.Dev.	(0.224)	(0.208)	(0.326)	(0.215)	(0.198)	(0.312)
Mother year of birth	Mean	1956.0	1957.9	1956.2	1955.7	1957.9	1956.0
	Std.Dev.	(8.140)	(7.719)	(8.116)	(8.303)	(7.751)	(8.270)
Risk aversion	Mean	5.630	5.722	5.639	4.958	4.955	4.958
	Std.Dev.	(1.732)	(1.785)	(1.737)	(1.708)	(1.731)	(1.710)
Mother working	Mean	0,594	0,577	0,592	0,576	0,543	0,572
	Std.Dev.	(0.428)	(0.411)	(0.426)	(0.434)	(0.422)	(0.432)
N		2202	1978	224	2106	1876	230

Note: The descriptive statistics describe the dependent variables as they are used in the correlation analyses. For the causal analyses samples are reduced to either consider older siblings or observations on paternal unemployment at an older age.
Source: SOEP (1984-2012).