Intergenerational Effects of Economic Distress: Paternal Unemployment and Child Secondary Schooling Decisions

PRELIMINARY AND INCOMPLETE - PLEASE DO NOT CITE[*]

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Abstract

Economic crises are particularly detrimental if they affect next-generation human capital. This paper investigates how paternal unemployment affects children's educational attainment and how much of this effect can be accounted for by psychological mechanisms. It uses variation in the local unemployment rate to identify the causal effect of individual unemployment.
The findings indicate that paternal unemployment a considerable negative effect on upper secondary school choice. Moreover, it adversely affects measures of child self-confidence in educational success, locus of control and mental health. These findings are consistent with a theoretical framework where paternal unemployment affects the return to education through the subjective probability of successful school completion.

JEL Classification: I20, J63, J64.

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1 Introduction

Does an economic crisis affect the next generation? A large body of literature shows that job loss reduces future earnings, future employment prospects, marital stability and (mental) health of the unemployed. However, if the children of the unemployed are equally affected, a crisis may have long run consequences on human capital. This study investigates how unemployment resulting from temporary shocks in the paternal labor market affects child schooling decisions.

There are at least two potential mechanisms that link paternal unemployment with child human capital. First, paternal joblessness may reduce parental monetary and non-monetary investments into child skills and competencies. Second, paternal unemployment may act as a temporary shock to a child's confidence in being able to graduate successfully if it occurs during a critical decision period. This study shows that paternal unemployment adversely affects children's educational choices but not immediate school performance if it occurs right before the schooling decision is made.

To understand the impact of labor market fluctuations and paternal unemployment on upper secondary schooling decisions, I estimate a latent variable model for the joint probability of paternal unemployment and child upper secondary school choice using the cyclical component in adult male unemployment as an exogenous shifter for paternal unemployment. I focus on paternal instead of maternal unemployment because the father tends to be the main breadwinner and because psychological effects of unemployment tend to be higher for men than for women (Theodossiou, 1998). Moreover, I show that the association between paternal unemployment and child schooling is much stronger for paternal than for maternal unemployment (for similar findings on the effects of paternal and maternal unmeployment, see Kalil and Ziol-Guest, 2008; Rege et al., 2011).

The decision whether to complete upper secondary schooling is vital in the German context. An upper secondary schooling certificate entitles individuals to a large range of white-collar vocational training positions and is a prerequisite for university attendance (Jenkins and Schluter, 2002). Children make this choice approximately at age 16, a time where they are still highly dependent and influenced by familial distress factors, such as parental unemployment.

The relationship between paternal unemployment and child education decisions cannot be investigated using experimental methods. Hence, a major concern is that paternal unemployment and child schooling may be jointly dependent on unobserved confounders. I address this concern by matching German household panel data with macro data on 97 regional economic centers for the years 1998-2009, including the years of the most recent crisis. I construct the cyclical component of regional labor market fluctuations in the labor market of the father and use this as an exogenous shifter for paternal unemployment. This identification strategy relies on the assumption that temporary unemployment shocks in the paternal labor market only influence child schooling decisions through paternal employment. This assumption is not innocuous if regional unemployment is correlated with youth unemployment. Therefore it is important to control for apprenticeship vacancies, youth unemployment, changes in the tax base as well as permanent unemployment in the region of residence. The underlying model also comprises indicators for urbanization, parental age and parental education and a number of other background variables because regions with different characteristics may be affected by recessions. After adding these control variables, I find that the null hypothesis of child schooling and paternal unemployment being independently determined by unobservables can no longer be rejected. Therefore, part of my results build on a matching assumption.

The data come from the German Socioeconomic Panel (GSOEP), a representative longitudinal micro-dataset that contains a wide range of socio-economic information on individuals in Germany, comprising yearly follow-ups during 1984-2010 (Wagner et al., 2007). Information on the children stem from a special youth survey comprising information on 17-year-old children of the responding households, collected in the years 2000-2010. The data are well-suited to my analysis because they can be linked to a large number of regional economic indicators and contain a vast number of parental and child characteristics. These allow me to study heterogeneity in the effect of paternal unemployment with respect to paternal cognitive ability, education, age, school tracks and gender. Moreover, detailed information on child characteristics and economic preferences allow me analyze several potential channels through which the paternal unemployment effect operates, such as the effect of paternal unemployment on expected school success.

The main finding of this paper is that paternal unemployment causally reduces offspring educational attainment and that a child's subjective probability of school success is an important mechanism. Detailed results are (1) the reduced form effect of a one percentage point increase in the cyclical component of regional unemployment amounts to a decrease in the probability of child upper secondary school choice by 2 percentage points, of a base level of 52%. (2) paternal unemployment lowers the probability of upper secondary school completion by 18 percentage points. (3) paternal unemployment reduces the subjective probability of successful school completion by 11 percentage points and if an individual believes that school completion is rather unlikely, the probability of upper secondary school choice decreases by 6.5 percentage points. After controlling for parental background variables, this subjective probability of school success accounts for 2 - 7.5 percent of the overall unemployment effect. (4) my findings can be explained by a theoretical framework that allows paternal unemployment to affect the assessment of the return to education through expected school success.

The contribution of this paper is threefold. First, it is the first paper that uses variation in the cyclical component of regional adult male labor market fluctuations as an exogenous shifter for paternal unemployment.[1] In a linear IV-setting with heterogenous effects, the effect I identify is thus a weighted local average treatment effect for children of individuals that suffer from unemployment due to a regional labor market downturn. This is the relevant effect for policy makers who want to obviate second order effects of an economic crisis (Carneiro et al., 2011). In this regard the paper is related to literature on other topics using regional unemployment shocks as exogenous shifters for endogenous variables (e.g., Ham and Jacobs, 2000; Ginja, 2010).

The second contribution of this paper is related to the use of household data. While most studies in this literature use administrative data with limited background information, household data allow me to investigate the impact of paternal unemployment on behavioral traits of the child and heterogeneity in the effect of paternal job loss for different groups of individuals. Whereas most of the existing literature focuses on income or parental investments as potential mechanisms (see e.g. Dahl and Lochner (2012), Blau (1999), Rege et al. (2011)) this paper innovates by laying the main focus on the psychological channels.

The fourth contribution is to explain my findings within a simple theoretical framework where paternal unemployment affects the return to education through the subjective probability of successful school completion. In this model children make upper secondary schooling decisions by comparing discounted wage flows for each schooling choice, where the high-education wage stream is weighted by the probability of actually achieving the higher education level. This study thus takes the standpoint of the child and does not focus primarily on parental investments.

The paper is organized as follows. Section 2 reviews the related literature and describes the institutional setting. Section 3 describes a simple framework that relates paternal unemployment with the subjective school success probability and child upper secondary education

[1] To my knowledge it is also the first paper to use cyclical macro variation for the most recent crisis years to investigate second order effects on next generation outcomes.

decisions. Section 4 describes the data, and Section 5 discusses the empirical estimation strategy and econometric models used. Section 6 presents the results of the analyses. Section 7 concludes.

2 Literature and Institutional Background

It is well-established that job loss has large adverse consequences on adult individuals. Recently, a limited number of studies have also investigated impacts of parental job loss on various child outcomes. I use household data that are ideally suited to answer the question at hand. Since these data were collected in Germany, it is important to understand the institutional context in which school decisions are made. Hence, Section 2.1 reviews the related literature whereas Section 2.2 and Section 2.3 describe the institutional labor market context as well as relevant parts of the education system.

2.1 Literature on paternal unemployment and child outcomes

A large number of studies investigate how unemployment and involuntary job loss affect individual well-being. Jacobson et al. (1993) and Ruhm (1991) find that permanent earnings of displaced workers are lowered by 25 and 10-13 percent respectively. It is also well-established that unemployment has quite dramatic effects on health, mental health and life satisfaction (Sullivan and Von Wachter, 2009; Eliason and Storrie, 2009; McKee-Ryan et al., 2005; Theodossiou, 1998; Kassenboehmer and Haisken-DeNew, 2009), and on family well-being, marital disruption and family relocation (Charles and Stephens, 2004; Astone and McLanahan, 1994; Kind and Haisken-DeNew, 2012).[2]

There exist relatively few studies that relate parental unemployment to child outcomes. Important exceptions are Oreopoulos et al. (2008), Bratberg et al. (2008) and Rege et al. (2011).[3] Rege et al. (2011) use Norwegian register data to estimate the causal effect of parental job loss due to plant closures during grade seven on the Grade Point Average (GPA) after grade ten. The analysis is based on a matching assumption and the authors

[2] McKee-Ryan et al. (2005), in a meta study summarizing 104 other studies, find large effects of unemployment but no significant effects of the current unemployment rate on mental health.

[3] Kalil and Ziol-Guest (2008) and Stevens and Schaller (2011) find that paternal job loss results in a higher probability of offspring grade retention in the Survey of Income and Program Participation (SIPP).Gregg et al. (2012) in a recent publication using the British Cohort Study Using the British Cohort Study find that children with displaced fathers obtain lower grades, lower wages and are at a higher risk of youth unemployment.

control for a large number of region, industry and school fixed effects. They find that paternal job displacement reduces GPA by 6 percent of a standard deviation, while maternal job loss leads to a nonsignificant increase in GPA. Furthermore, the effect is largest in municipalities with non-decreasing unemployment rates and below median pre-closure earnings. Focusing on paternal investment channels, the authors report that the effect of paternal job loss does not pass through subsequent earnings or time allocation of mothers, divorce or residential reallocation. Therefore, the authors conclude that parental mental health is the driving mechanism. A second paper by Bratberg et al. (2008) uses Norwegian data, too, and investigates the effect of paternal displacement when children are of age 12-16. The authors analyze matched employer-employee panel data and find no significant effects on earnings, non-employment or registered unemployment of the next generation. The third paper uses information about plant closures in Canadian administrative data (Oreopoulos et al., 2008). The authors show that sons in the age group 10-14 of displaced workers have adult annual earnings that are about 9 percent lower than similar children of fathers who did not experience an employment shock. The effect is largest for families in the lowest quartile of the income distribution. When it comes to mechanisms, they find displacement to slightly affect mobility but mobility not to affect child outcomes. Moreover, their results indicate that displacement does not affect marital status or spousal income. Therefore, Oreopoulos et al. (2008) conclude that income is the driving mechanism. The results of these studies are specific to individuals affected by plant closings. Also, fathers employed at closing plants are likely to be less skilled at foreseeing the future or less willing to change jobs when firms start to deteriorate economically (Pfann and Hamermesh, 2001).

From a methodological point of view, this paper is close to other studies that use exogenous variation as a shifter for unemployment or family resources. Examples are Ham and Jacobs (2000) who use the unemployment rate in the household head's occupational category as an instrument for family resources or Fougère et al. (2009) and Gould et al. (2002) who use predicted changes in employment shares of different demographic groups in different regions as instruments for youth unemployment.

A large body of literature studies the effects of parental income and maternal employment patterns on child outcomes (Blau, 1999; Dahl and Lochner, 2012).[4] These studies find that the effect of income on child development is significant but modest, and less important than child characteristics and other family background variables.[5]

[4]Maternal employment tends to have small negative effects, especially while the children are small (Ruhm, 2004).

[5]Jenkins and Schluter (2002) also find small income effects for child achievement in Germany.

2.2 Institutional changes and the German labor market during the great recession

The exogenous variation used in this paper comes from temporary unemployment shocks, and the identification of the model is based on temporary employment fluctuations. Therefore, it is important to note that the period under study includes the 2008/2009 world recession. The crisis has hit Germany harder than most other OECD countries as demand for the Germany's exports plummeted during the crisis. However, despite a 5% drop in GDP, labor market effects were less dramatic than in many other European countries. There were almost no mass layoffs and no general feeling of panic. Assisted by short-time work schemes, many firms buffered capacity (Möller, 2010).

German industries were affected very unequally by the crisis. Overall, only 37% of firms reported to have felt the negative effects of the crisis, but as many as 70% of metal producers (Möller, 2010). Because many of these producers are located in Western and Southern Germany, some areas in these parts of the country were quite heavily affected. At the same time, these were regions that had been particularly strong before the crisis (Fuchs and Kempermann, 2011).

The period under investigation comprises the so-called Hartz reforms (I to IV) between 2003 and 2005, which was a substantial reform of the unemployment benefit system that lead to an increase in unemployment hardship. In 2005, unemployment and social assistance were merged into a single means-tested welfare payment. Since then, eligibility for unemployment benefits depends on being physically and mentally capable of working for at least 15 hours per week, active job search and the willingness to participate in welfare to work programs. Moreover, non-compliance to the unemployment benefit rules or the rejection of job offers can be sanctioned by means of temporary benefit cuts (Huber et al., 2011). The reforms have lead to a decline in the natural rate of unemployment by increasing the incentives for unemployed to search for and accept new jobs.

2.3 School choice in the German context

School choice at age 16 is an important stepping stone towards obtaining an upper secondary school degree (Abitur/Fachabitur). Taking 2-3 years to complete, it serves as a school graduation certificate and university entrance exam. Moreover, it grants access to colleges and universities and is a prerequisite for many apprenticeship and vocational training positions.

Individuals who do not complete an upper secondary school degree mostly continue vocational training and eventually take up work in blue collar occupations.

Upper secondary school choice in Germany is influenced by a system of early tracking. At age 10-12, children are tracked into one of three separate hierarchical school strands. Although, formally, students from all three tracks can obtain an upper secondary school degree, the latter is more difficult if tracked into Haupt- or Realschule (the lower tracks) than Gymnasium (the highest track) (Jenkins and Schluter, 2002).

Results by **?** imply that, at least for individuals at the margin, tracking is less decisive for obtaining a certain educational degree than upper secondary school choice itself. This is explainable by the substantial amount of student up- and downgrading between track types at the time of upper secondary school choice (**?**). At that time, individuals holding a German general secondary school degree (Hauptschulabschluss) or a German intermediate school degree (Realschulabschluss) can obtain an upper secondary school degree (Fachabitur or Abitur) if they change school after grade 10 or if they graduate from specialized vocational schools.

Rules and regulations concerning degrees and compulsory schooling ages vary greatly between the different federal states. While, in most states, schooling is compulsory until age 18 (secondary school + vocational school), some states only require 9 years of schooling.[6] Furthermore, secondary general schools finish after grade 9 in most federal states and after grade 10 in others. When investigating the impact of paternal unemployment at child age 16, it is thus very important to control for state of residence.

3 A Theoretical Framework for the Impact of Paternal Unemployment on Child Upper Secondary School Choice

Education choices are pivotal to the amount of human capital an individual accumulates in life. While skills and abilities are predominantly a function of parental investments during early childhood, human capital accumulation is essentially a matter of own choice at later ages. Section 3.1 considers a simple theoretical framework where each individual chooses between obtaining upper secondary education or not. Paternal unemployment influences this

[6] These are Saarland, Thuringia and Hesse.

choice through its impact on the subjective probability of upper secondary school success as laid out in Section 3.2.

3.1 A human capital investment model

The effect of paternal unemployment can be incorporated into a Roy model of human capital investment decisions where individuals weigh the discounted flow of wages of the upper secondary school degree wage path with the subjective probability of being successful at obtaining the degree.

In a typical model of human capital investment, individuals make human capital investment decisions based on the present value of future wages (Becker, 1993). Individuals weigh the benefits of continued upper secondary schooling against the benefits of dropping out at age 16 when they decide whether to continue schooling.

Assume that there are two education levels, $S = \{0, 1\}$, where $S = 1$ denotes holding an upper secondary school degree and $S = 0$ denotes all lower education levels. Furthermore, suppose that there are two wage paths w^l and w^h over T periods of time, where $w^l(t)$ represents the wage in period t for a low educated individual and $w^h(t)$ represents the wage in period t of an individual who holds an upper secondary school degree. Assume that, while wage path l can be obtained with certainty, wage path h depends on successful school completion ($S = 1$) which is uncertain. That is, at age 16, an individual cannot be sure she will be successful at obtaining the corresponding degree whether after 2-3 years. Let $p \in [0, 1]$ denote the subjective probability of successful upper secondary school completion at age 16. Expected future wages conditional on choosing the high schooling path then depend on p according to:

$$\mathrm{E}\big[w^{S=1}(t)\big] = pw^h(t) + (1-p)w^l(t) \tag{3.1}$$

If an individual chooses to drop out at age 16, this implies $p = 0$ and:

$$\mathrm{E}\big[w^{S=0}(t)\big] = w^l(t). \tag{3.2}$$

In that case the low wage path is a deterministic process from the point of view of the individual.

Agents maximize the expected net present value of education to make their decision. Let V^* denote this latent variable. Then an individual attends upper secondary schooling, $S = 1$, if:

$$V^* \;\geq\; 0,$$

and $S = 0$ otherwise. Using Equations 3.1 and 3.2, the net present value of upper secondary schooling, accounting for the discounted flow of ex post earnings is:

$$V^*(w^1, w^0, \delta, t_s, p) = \sum_{t=t_s}^{T} \delta^t \mathrm{E}\big[w^1(t)\big] - \sum_{t=0}^{T} \delta^t \mathrm{E}\big[w^0(t)\big]\,, \tag{3.3}$$

where t_s represents the time required to achieve upper secondary schooling, T is the life horizon, and δ denotes the discount rate, which for is assumed to be constant over time for simplicity. If the decision process is also influenced by monetary costs of upper secondary school choice, such costs would be subtracted in Equation (3.3). However, German schools are almost exclusively public and do not charge fees. One can estimate the effect of an individual's characteristics on the probability of an individual to choose upper secondary schooling school with a reduced-form model using variables that influence earnings, determines the discount rate, δ, and determine the subjective probability of obtaining an upper secondary schooling certificate.

3.2 The role of paternal unemployment

Teenagers whose fathers become unemployed are likely to receive a temporary shock to their mental health, self-confidence and locus of control. Furthermore, these children may expect that school support and assistance of their parents will go down in the future. Paternal unemployment therefore reduces the subjective success probability p of obtaining an upper secondary school degree:

$$p(D = 1) < p(D = 0) \tag{3.4}$$

where $D = \{0, 1\}$ denotes paternal unemployment. It is easy to see that the net present value of upper secondary schooling is increasing in p as long as wages in the high education sector are higher than in the low education sector:[7]

$$\frac{\partial V^*(w^1, w^0, \delta, t_s, p)}{\partial p} = \sum_{t=t_s}^{T} \delta^t \left[w^h(t) - w^l(t)\right] > 0 \tag{3.5}$$

[7]Implicitly I assume that t_e is low enough, such that, if $p = 1$, education pays off in general.

It follows that paternal unemployment has a negative effect on the net present value of upper secondary schooling:

$$\frac{\Delta V^*}{\Delta D} < 0. \tag{3.6}$$

If p can be observed by the econometrician, this simple theoretical framework provides a testable mechanism for the effect of paternal unemployment on upper secondary school choice. Note that I make the assumption that paternal unemployment at age 16 does not have a direct impact on wages or the discount rate of individuals. This is a strong assumption, which fails to hold, for example, if paternal unemployment has a differential impact on an individual's work related skills needed in either of the two wage sectors. Note also that, in order to be able to use fluctuations in the local unemployment rate as an exclusion in the schooling equation, I need to make the assumption that future wage paths are not influenced by labor market fluctuations. E.g., my results would be biased upwards if a recession today permanently reduced wages more along the high education wage path than along the low education wage path. Research shows that temporary labor market downturns can indeed have lasting impacts but that the effect is larger for lower educated workers (Oreopoulos et al., 2012). This research shows that it is important to control for youth unemployment and the availability of vocational training positions.

4 Data

I match German representative household data with labor market information on 97 regional economic centers for the years 1998-2009. Section 4.1 describes the dataset and Section 4.2 explains the coding of the main variables. Section 4.3 lays out how I construct the cyclical component of adult male unemployment in the paternal labor market, and Section 4.4 describes the sample.

4.1 Dataset and sample construction

My sample is drawn from the German Socioeconomic Panel (GSOEP), a representative longitudinal household dataset that contains a wide range of socio-economic information on individuals in Germany comprising follow-ups for the years 1984-2010. Information was first collected in 1984 for about 12,200 randomly selected adult respondents in West Germany. After German reunification in 1990, the GSOEP was extended to around 4,500 persons from East Germany, and subsequently supplemented and expanded by additional samples.

This study draws on 3,138 individuals, born 1983-1993, from the GSOEP "youth survey", covering the children of all GSOEP panel members. A comprehensive set of background variables, schooling choices, preferences, opinions and traits of these individuals were collected over the years 2000-2010, when the subjects were 17 years of age.

The data provide four advantages. First, using a household's region of residence, the data can be matched with regional labor market information as well as a large battery of other regional measures, such as regional tax income or regional development indicators. Second, the data contain information on youth upper secondary school choice one year after the decision was made, such that revealed education preferences can be observed. Third, the youth data can be linked to detailed parental information including parental investments, skills, living patterns, labor force participation and unemployment histories. Fourth, the data contain rich information on child traits as well as the subjective probability of an individual to successfully complete her education.

I use the following sample selection criteria. First, I exclude all individuals who in elementary school received a track recommendation for the lowest track. The reason is that in most federal states the low-track schools only take 9 years to complete. Moreover, individuals in the lowest track may lack the cognitive ability or opportunity to obtain an upper secondary school degree. Second, I only include individuals who live in the same household with both of their parents. Third, I exclude individuals for which paternal unemployment in the previous year is missing. Fourth, some subjects were already 18 or 19 years of age when first completing the questionnaire in 2001. I exclude these individuals from the sample. Moreover, I also drop individuals with implausible values for paternal age, missings for the subjective school success probability (very few) and missing regional indicators.[8] Last, I exclude all students with missing information in any of the covariates displayed in Table 3. Table 1 displays the final sample size (N=2,326), the fraction of individuals who choose upper secondary schooling and the fraction of individuals whose father is unemployed when they are 16 years of age. 52% of all individuals in the sample have chosen upper secondary education, compared to an average of 54% in Germany (in 2012) (OECD, 2012). The unemployment rate of 10% for the fathers in the sample is slightly higher than the average official unemployment rate of 9.6% over that period, which is due to the fact that I also include non-employed fathers who are currently not part of the labor force. The third reports the mean and standard deviation of the cyclical component of regional unemployment in the paternal labor market.

[8] I drop all individuals with fathers who are younger than 32.

Table 1: Proportions of Youths with higher education (*outcome*), paternal unemployment (*treatment*) and cyclical component of regional unemployment in paternal labor market (*exclusion*)

	Youths, age 17		
	Proportion	**SD**	**N**
Upper_secondary_education	.52	.5	1205
Father_unemployed	.1	.296	225
Regional_unemployment	.66	1.377	2326

Source: GSOEP youth sample 2000-2010.

4.2 Coding of main variables

Upper secondary school choice is the main outcome of interest. This study classifies all individuals as having chosen upper secondary education, if according to the international Comparative Analysis of Social Mobility in Industrial Nations (CASMIN), they have an education level that corresponds to CASMIN-categories (2c), (3a) or (3b).[9] Here, I use the latest available information. Furthermore, all youths who have not yet completed their education at the time of the last interview are classified as having chosen upper secondary education if they are still in school and are planning to take an upper secondary school exam that entitles them to enter a teaching college or university (German Abitur or Fachabitur) at the time of the interview.[10]

Paternal unemployment is the central explanatory variable. Fathers are classified as unemployed if they are not working at the time when the child is 16 years of age. This also discouraged workers who are not currently looking for a job count as unemployed. The assumption behind this is that voluntary unemployment among the fathers of school age children is rare. Business cycle fluctuations and sanctioning (see Section 2.3), on the other hand, may cause part of the unemployed workforce not to actively search for a job. Table 2 displays raw correlations between upper secondary school choice and a variable that indicates whether father or mother became unemployed in the past year. The table shows that (a) in terms of correlations, it hardly matters whether all unemployed or only those actively searching for a job are classified as unemployed;[11] (b) The association between paternal un-

[9]See Section 2.3 for a description of the German institutional context.

[10]A second measure of upper secondary schooling is whether an individual is still at school at age 17. This measure is used for robustness checks.

[11]All robustness checks show that the results with this coding of unemployment are conservative. If only those individuals are classified as unemployed who are not working and actively looking for a job, coefficients increase slightly and become somewhat more significant.

employment and school choice is three times as large as between maternal unemployment and school choice.[12]

Table 2: Raw correlation: paternal/maternal change to non(un-)employment and child upper secondary schooling

Newly unemployed	**Upper Secondary Education**
Father becomes unemployed	-0.3160***
	(0.053)
Father becomes involuntarily unemployed	-0.3472***
	(0.050)
Mother becomes unemployed	-0.1167**
	(0.057)
Mother becomes involuntarily unemployed	-0.1024
	(0.068)
Observations	2120 (father) 2092 (mother)
Covariates included	NO

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Standard errors are robust.
Raw correlations displayed, no covariates included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The subjective probability of school success is the main potential mechanism of interest. In the youth survey, individuals are asked "What is the probability that you will successfully complete your training or further studies?"[13] Individuals can indicate a probability in decimal steps. Note that the question is framed rather broadly and does not specifically address upper secondary schooling. Yet, what this study is interested in is whether an individual loses confidence in her abilities to complete further education or training due to paternal unemployment, which this question should adequately capture. I use the subjective probability as described above as well as an indicator variable $\mathbb{1}\left[Percentage > 50\right]$ for whether an individual believes she is rather likely to complete her education.

To be able to control for childhood circumstances, I construct a large set of background variables comprising parental age, family size paternal education, parental investment variables, nationality and region. Moreover, in order to proxy cognitive skills and to account for the fact that schooling decisions may depend on prior track attendance (see Section 2.3), I include an individual's track recommendation after elementary school. In Germany, every student receives a track recommendation during 4th grade by her elementary school teacher. In most German states, track recommendations are non-mandatory. In some states they are compulsory. Last, I construct time and state fixed effects.

[12]Table D.1 repeats the same correlations with GPA instead of upper secondary school choice and shows that there is no significant negative association between parental unemployment and child GPA as defined by the average of the most recent grades obtained in German, math and first foreign language.

[13]"Wie wahrscheinlich ist es, dass Sie Ihre Ausbildung oder Ihr Studium erfolgreich abschließen?"

4.3 Regional labor market information

Using individual identifiers for 97 regional economic centers in Germany, I match the GSOEP data with external data on local economic and labor market variables for the year in which the child was 16 years old.[14] Macro variables are obtained from the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (Bundesinstitut für Bau-, Stadt- und Raumforschung (BBSR) im Bundesamt für Bauwesen und Raumordnung (BBR), 2011). Specifically, I take the regional unemployment for male individuals in the age group of the father and deduct mean unemployment in that region over the entire observation period. Besides, I use year fixed effects in all specifications to account for institutional changes and country-wide shocks over time.[15] The exogenous labor market shifter is given by:

$$Z_{t,r,a} = A_{t,r,a} - \mu_{r,a},$$

where $Z_{t,r,i}$ denotes the cyclical component of adult male unemployment in year t, region r and age group a. The average unemployment rate $\mu_{r,a}$ is given by:

$$\mu_{r,a} = \frac{1}{T} \sum_{t=1}^{T} A_{t,r,a} \qquad \text{for } t = 1998, ..., 2009$$

Region-age-gender specific unemployment rates imply, for example, that, if the father is 56 years of age, the unemployment rate A_t is given by the regional unemployment rate for males aged 55+.[16] Fluctuations in the regional unemployment rate for older men are included in the data, because they are likely correlated with youth unemployment, taxed-based school financing and the availability of apprenticeship training positions.

4.4 Characteristics of the sample

Table 3 summarizes characteristics of the pooled sample of the 2,326 youths I analyze. The summary statistics clearly show that the children of unemployed fathers differ from

[14]A map of the 97 labor market regions is displayed in Figure E.1. These regions are planning entities of the federal states in Germany and borders were drawn such that they reflect local labor markets and commuting areas. The regions in this study are thus comparable to US commuting zones (see e.g. Autor and Dorn, 2009).

[15]See Section 2.2.

[16]An alternative way of defining the cyclical component of regional labor market fluctuations would be to subtract trend unemployment, as computed using the Hodrick-Prescott Filter. However, due to the extremely short time series available for each region, this approach would be dominated by endpoint problems. Robustness checks show that the results are robust to this alternative definition.

Table 3: Summary statistics, background variables

Variables	Youths		
	Father employed	**Father unemp**	**P-value**
Outcome			
Secondary schooling	0.55	0.25	0.00
Background variables			
Maternal age	44.54	44.56	0.95
Paternal age	47.04	49.14	0.00
One sibling	0.50	0.28	0.00
Two siblings	0.26	0.30	0.17
Three or more siblings	0.12	0.28	0.00
Father secondary intermediate	0.33	0.25	0.03
Father grammar school	0.31	0.16	0.00
Mother secondary intermediate	0.45	0.30	0.00
Mother grammar school	0.25	0.14	0.00
Childhood in large city	0.20	0.24	0.13
Childhood in medium city	0.19	0.20	0.55
Childhood in small city	0.27	0.23	0.21
Sex, male=1	0.51	0.48	0.46
Permanent component of unemployment	7.36	8.21	0.00
German nationality	0.95	0.84	0.00
Father has German nationality	0.92	0.80	0.00
Father cognitive skills	0.11	-0.30	0.00
Youth local labor market (mean deviation)			
Vocational training positions per 100 applicants	-0.78	-0.74	0.85
Youth unemployment	0.07	0.20	0.03
N	2326		

Source: SOEP youth data, waves 2000-2010. Own calculations.
Notes: p-values of a two-sided t-test for differences in means are reported.

children of employed fathers in almost all characteristics. First, only 25% of the children of unemployed fathers choose upper secondary schooling, while these are 55% among families with employed fathers. Individuals with unemployed fathers tend to have more siblings, older fathers, less educated parents, fathers with lower cognitive skills, and are more likely to have a non-German background. Concerning child characteristics, Table 4 shows that children of jobless fathers are less likely to believe that they will successfully complete their education and display a significantly lower locus of control and a lower GPA.[17] Youth mental health is measured by the Mental Component Summary Scale (MCS), one of the two sub-dimensions of the SF-12 questionnaire and risk aversion is measured by an individual's willingness to take risks (for a description of the risk measure see Dohmen et al., 2011). Locus of control, youth mental health and risk aversion are standardized to have mean zero and standard deviation one. GPA is coded by averaging last school grades in math, German and their first foreign language. German grades have been reversed now ranging from 1 to 6 where more is better. Certainly, some of the observed difference in child upper secondary schooling cannot be ascribed to the causal effect of unemployment but is driven by observed and unobserved confounders. Panel (a) of Figure 1 provides a graphical assessment of the average difference

[17] For a description of the locus of control measure and underlying construct in the GSOEP see Piatek and Pinger (2010).

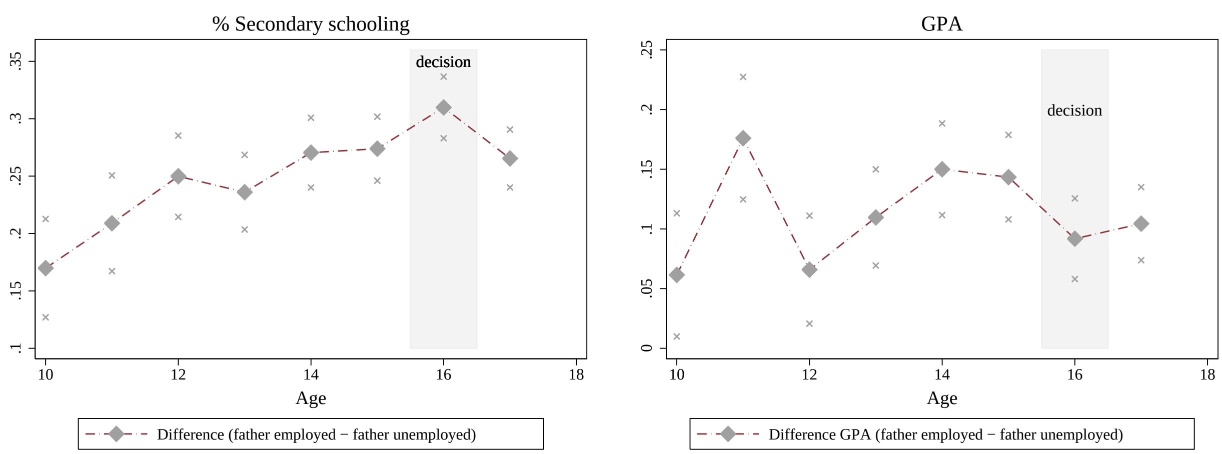
Table 4: Summary statistics, subjective school success and child traits

Variables	Youths		
	Father employed	**Father unemp**	**P-value**
Subjective school success			
Probability, successful school completion	78.59	74.67	0.00
Probability, successful school completion>50 %	0.88	0.81	0.01
Child trait channels			
Youth mental health	-0.01	0.12	0.07
Youth risk aversion	-0.01	0.04	0.52
Youth locus of control	0.02	-0.21	0.00
GPA			
Youth grade point average	0.02	-0.11	0.08
N	2326		

Source: SOEP youth data, waves 2000-2010. Own calculations.
Notes: p-values of a two-sided t-test for differences in means are reported.

in upper secondary schooling probability between youths whose fathers were employed or unemployed at different ages of the child. The graph shows that this difference in outcomes increases the closer in time paternal unemployment occurs to the education decision of the child. This indicates a likely causal effect of unemployment. Panel (b) shows that no such relationship exists when looking at child GPA as an outcome.

Figure 1: % upper secondary schooling and GPA by paternal employment status and age.



(a) Upper secondary schooling

(b) GPA

Notes: GSOEP youth sample 2000-2010. Sample contains all individuals whose parental unemployment history is available for at least the past 3 years.

5 Estimation strategy

The theoretical framework of Section 3 has shown that paternal unemployment is likely to reduce the probability of upper secondary schooling and that the perceived probability of school success is a crucial parameter for the decision about upper secondary schooling. This section explains how I identify and estimate (a) the overall causal effect of paternal unemployment, (b) a latent factor model for paternal cognitive ability, (c) the direct, indirect and total effect of paternal characteristics, (d) the effect of paternal joblessness on the subjective school success probability, and (e) the impact of that probability on schooling decisions.

5.1 Simultaneous equation bivariate probit model

The utility of upper secondary schooling and the disutility of unemployment are unobserved latent variables, for which only final outcomes are observed. Because unobservables that drive paternal unemployment (D) and child secondary school choice (E) are likely to be correlated, it is important to jointly estimate the probability of paternal unemployment and of child upper secondary schooling. The model is:

$$\begin{aligned} U^*_{S,i} &= \beta D_i + \alpha'_S X_i + \sum_{r=1}^{R} \gamma_S d_{r,i} + \sum_{t=1}^{T} \tau_S d_{t,i} + \lambda_S \theta_i + \epsilon_{S,i}, \quad S_i = \mathbb{1}\left[U^*_{S,i} \geq 0\right] \\ U^*_{D,i} &= \alpha'_D X_i + \delta Z_i + \sum_{r=1}^{R} \gamma_D d_{r,i} + \sum_{t=1}^{T} \tau_D d_{t,i} + \lambda_D \theta_i + \epsilon_{D,i}, \quad D_i = \mathbb{1}\left[U^*_{D,i} \geq 0\right], \end{aligned} \tag{5.1}$$

where U^*_S and U^*_D denote latent (dis-)utility from education and unemployment respectively. X is a vector of background variables, Z denotes the cyclical component of adult male unemployment as defined in Section 4.3, and θ is latent paternal cognitive ability. $d_{r,i}$ and $d_{t,i}$ denote state (or region) and time dummies. A list of all included explanatory variables in each equation is given in Table 6. $(\epsilon_{S,i}, \epsilon_{D,i})$ are jointly distributed as standard bivariate normal with correlation ρ and independent of Z. I use standard maximum likelihood methods to estimate the parameters β, δ, α_D, α_S, λ_D, λ_S, γ_S, γ_D, τ_S, τ_D and ρ.[18] I compute standard errors that are robust and clustered at the level of the regional economic centers. For each

[18] The likelihood is given by:

$$\ln L = \sum_{i=1}^{N} \ln \Phi_2(a_{i,S}, a_{i,D}, \rho)$$

where Φ_2 denotes the bivariate normal cdf, $a_{i,S} = (2S-1)(\beta D_i + \alpha'_S X_i + \sum_{r=1}^{R} \gamma_S d_{r,i} + \sum_{t=1}^{T} \tau_S d_{t,i} + \lambda_S \theta_i)$ and $a_{i,D} = (2D-1)(\alpha'_D X_i + \delta Z_i + \sum_{r=1}^{R} \gamma_D d_{r,i} + \sum_{t=1}^{T} \tau_D d_{t,i} + \lambda_D \theta_i)$.

model, I conduct a Likelihood Ratio (LR) test for the absence of correlation in the model under the null hypothesis that ρ equals zero. If the null hypothesis cannot be rejected, I report parameters of a restricted model with $\rho = 0$.

There is a large number of different marginal effects that can be computed for this model. I compute average marginal effects for the unconditional probability that $S = 1$ (or $D = 1$), which is the effect of interest in this study. The marginal effect for continuous covariates is given by:

$$\frac{\partial \mathrm{E}[S|\mathbf{x}]}{\partial \mathbf{x}} = \Phi(\mathbf{x}'\zeta)\zeta, \tag{5.2}$$

where $\mathbf{x}$ denotes a combined vector of all explanatory variables and ζ a vector of all coefficients, some of which may be zero for variables that only appear in the other equation. For discrete variables, finite differences are computed. Standard errors of the marginal effects are bootstrapped using 200 bootstrap replications.

5.2 Latent factor model

In order to account for paternal cognitive ability, I use a factor model as an integral component of the simultaneous equation model described above. Paternal cognitive skills are assumed to depend on multiple measures M_k where $k \in \{1...K\}$ and K is the total number of measures available.

A factor model is necessary here to account for the fact that different measurements are going to be correlated to a different degree with the latent construct. In a factor model, different weights, called factor loadings, are estimated. By estimating a factor model, one can account for measurement error in proxies and avoid attenuation bias. The cognitive skill measurement system is:

$$M_{Ck,i} \quad = \quad \lambda_{Ck}\theta_{C,i} + \epsilon_{Ck,i} \qquad \text{for } k = 1, ..., K.$$

where λ_{Ck} are factor loadings associated with measurement k. Factor loadings are allowed to differ across equations giving measurements different weights. Since the scale of each factor is arbitrary, I restrict the variance of the factor to equal unity and require $K > 2$ for identification. In addition, $\mathrm{E}[\epsilon_{\theta_C k}] = 0$ and $\mathrm{E}[\theta_{C,i}] = 0$. I use the Bartlett method to obtain unbiased factor scores (Bartlett, 1937).

Cognitive skills are measured using a test of symbol correspondence (administered in 2006) that was specifically developed for the GSOEP and corresponds to a sub-module of the

Wechsler Adult Intelligence Scale (Lang et al., 2007). Missing cognitive ability measures were imputed on hands of information about an individual's education as well as family education measures using linear regression.

Table 5: First stage regression of paternal unemployment on the age-specific regional unemployment rate

Paternal unemployment	**All**	
	OLS	**Probit**
Cyclical component of adult male unemployment	0.01476***	0.01294***
	(0.005)	(0.004)
Observations	2326	2326
Covariates included	YES	YES
F-stat (β (instrument)=0)	9.673	
R-squ adj./Ps R-squ.	0.086	0.139

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Standard errors clustered by region. Coefficients of probit equations are average marginal effects. The analytical sample on which these estimates are based consists of all GSOEP youths that have no missings in any of the covariates. For covariates included see Table 6.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Linear IV

To investigate the effect of paternal unemployment on the subjective probability of school success, child mental health and locus of control, I use the Two-Stage-Least-Squares (2SLS) estimator with paternal unemployment as a treatment and the cyclical component of adult male unemployment in the region as an instrument. The estimator is:

$$\beta_{2SLS} = (\hat{D}'\hat{D})^{-1}\hat{D}'Y, \tag{5.3}$$

where Y denotes the outcome of interest and $\hat{D} = Z(Z'Z)^{-1}Z'D$. To use Z as an exclusion in Equation (5.1) or as an instrument in Equation (5.3), it is important that the reginal labor market instrument is informative. Table 5 shows the results of a linear regression model and of a probit model, where the dependent variable is paternal unemployment. In both cases, the instrument is highly significant and the F-statistic of a test for $\delta = 0$ is close to 10.

5.4 Decomposition of the unemployment effect

In order to investigate how much of the overall gap in different upper secondary school choice probabilities is due to differences in the subjective probability of school success or due to other child characteristics, I use a nonlinear decomposition in the spirit of Fairlie (2005). It is the same decomposition used and described in Heckman et al. (2013) except for nonlinear models. Assume that school choice is independent across children of employed and unemployed fathers conditional on a large vector of exogenous variables X that are not affected by paternal unemployment. The decomposition is based on the following non-linear probit model:

$$P(S_i^D = 1|X_i^D, p_i^D) \quad = \quad \Phi({\alpha_S}' X_i^D + \eta p_i^D), \quad with \quad D \in \{0, 1\} \tag{5.4}$$

where region and time dummies are also controlled for, but excluded from Equation 5.4 for notational simplicity. X_i^D is a vector of all background characteristics listed in Table 6 and p_i again denotes the subjective success probability of individual i. The above equation implies the assumption that the effect of background characteristics and the subjective school probability is the same for individuals of employed and unemployed fathers $\alpha_S^0 = \alpha_S^1$ and $\eta^0 = \eta^1$. I test and do not reject this hypothesis.

The goal of the decomposition is to decompose the effect of paternal unemployment into components attributable to a change in the subjective school success probability. Following the notation used in Fairlie (1999) and using coefficients from a probit regression for a pooled sample, the contribution of p to the different in school choice probabilities $\Delta\bar{S}$ between children of employed ($D = 0$) and unemployed ($D = 1$) fathers can be written as:

$$\Delta\bar{S}_p = \sum_{i=1}^{N^1} \frac{1}{N^1} \Phi({\alpha_S}' X_i^0 + \eta p_i^1) - \Phi({\alpha_S}' X_i^0 + \eta p_i^0)^{19} \tag{5.5}$$

The contribution of each variable to the in upper secondary school choice probabilities is thus equal to the change in the average predicted probability from replacing the distribution of the subjective school success probability for children of unemployed fathers with the one of children from employed fathers. To this end both samples are matched on the basis of their rank in the distribution of school choice probabilities. Because there is a lower number of children from unemployed fathers a number of 100 repeated random subsamples of children from employed fathers are drawn and matched to compute Equation 5.5.

[19] In practice the value of $\Delta\bar{S}_p$ depends on whether background variables are fixed at $X_i^D = 0$ or X_i^1. To account for this a random ordering of variables is used.

The percentage of the unemployment effect explained by p which cannot be accounted for by background variables can then be expressed as a percentage of the observed difference in school choice probabilities that cannot be accounted for by the exogenous variables. For most models this amounts roughly the percentage of the treatment effect explained by p. In addition I express p as a percentage of the treatment effect computed in Equation 5.1 (to be done!).

Table 6: Covariates in the different model equations

		Unemployment	Upper secondary schooling
Covariates	Constant	✓	✓
	Paternal age	✓	✓
	Maternal age		✓
	2 children	✓	
	3 children	✓	
	4 or more children	✓	
	1 sibling		✓
	2 children		✓
	3 or more siblings		✓
	Father secondary intermediate school	✓	✓
	Father grammar school	✓	✓
	Mother secondary intermediate school	✓	✓
	Mother grammar school	✓	✓
	Father German	✓	
	Large city	✓	✓
	Medium city	✓	✓
	Small city	✓	✓
	Permanent unemployment component		✓
	Father industry dummies	✓	✓
	Youth sex (male=1)		✓
	Youth German		✓
	Youth track recommendation		✓
	Father cognitive ability	(✓)	(✓)
	Vocational training positions per applicant in region		(✓)
	Youth unemployment in region		(✓)
	Subjective school success probability		(✓)
	Year FEs	✓	✓
	Federal state FEs	✓	✓
	Region FEs	(✓)	(✓)

Note: Covariates in brackets only included in some specifications.

6 Empirical results

The results are presented and discussed in several stages. I first provide a description of the main findings in Section 6.1, including the reduced form effect, the causal effect of paternal unemployment and a comparison of the secondary school choice results with results for child GPA. Section 6.2 elicits further results displaying the heterogeneity of the paternal unemployment effect for different groups of children and families. Section 6.3 presents the impact of paternal unemployment on child traits and the subjective school success probability, as well as the effect of their effect on upper secondary school choice. Section 6.4 elaborates on some robustness checks.

6.1 The effect of paternal unemployment on education choices and GPA

If labor market fluctuations influence secondary school choice via paternal unemployment, one would expect to find an association between the cyclical component in regional adult male unemployment and child upper secondary school choice. Columns (1) and (2) of Table 7 show that, after controlling for background variables, the linear reduced form effect of an increase in the unemployment rate of the paternal labor market leads to a reduction in the probability that a child chooses upper secondary schooling by a little more than two percentage points.[20] This effect remains strong even after controlling for youth unemployment and the number of vocational training positions per applicant in the region.[21] The effect of unemployment fluctuations in the maternal labor market, on the other hand, displayed in columns (3) and (4), is close to zero and insignificant. The reason for why child school choice and unemployment in the maternal labor market are unrelated after controlling for background variables is probably that (a) female employment decisions are correlated less with local labor market developments, and (b) the association between maternal unemployment and child schooling decisions is lower than for paternal unemployment.

Table 7: Reduced form regressions

reduced form	**Upper Secondary Education**			
Cyclical component of adult male unemployment	-0.0228**	-0.0237**		
	(0.011)	(0.011)		
Cyclical component of adult female unemployment			0.0005	0.0005
			(0.000)	(0.000)
Observations	2326	2326	2326	2326
Covariates included	YES	YES	YES	YES
Labor market controls included	NO	YES	NO	YES
R-squ adj./Ps R-squ.	0.202	0.202	0.201	0.201

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Standard errors are robust. Covariates are sibling dummies, parental education, size of region, nationality, year FEs, region FEs.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[20]See also Figure E.6 for a graph of the raw association between regional unemployment fluctuations and paternal unemployment and child schooling decisions, respectively.

[21]This strong reduced form effect is consistent with findings by Rampino and Taylor (2012) who report that changes in the unemployment rate have an effect on youth attitudes towards schooling in Britain.

Going beyond the reduced form estimation, I use a simulatenous equation bivariate probit model to assess the causal effects of paternal unemployment on child upper secondary school choice. The first row of Table 8 displays the average marginal effect of paternal unemployment on child upper secondary school choice for different model specifications. Paternal unemployment reduces the probability of upper secondary school choice by around 18 percentage points. This effect seems very robust even after including youth labor market and vocational training measures, paternal cognitive skills and several interaction effects. The latter comprise cross terms between paternal unemployment and paternal schooling, paternal cognitive skills and paternal age on the one hand, and between paternal labor market fluctuations and the three paternal traits, displayed in lines 2-4 on the other hand. The table also displays the estimated marginal effect of unemployment fluctuations in the second equation of model (5.1). It shows that a one percentage point increase in the cyclical component of adult male unemployment translates also into a one percentage points higher unemployment probability among the fathers in my sample.[22] Note that the LR-test does not reject the null hypothesis of $\rho = 0$ for any of the models displayed in the table. Hence, marginal effects of a restricted model are presented.[23]

Table 9 repeats the analysis of Table 8 for child GPA as a dependent variable, using the linear IV estimator and OLS.[24] The IV results suggest that paternal unemployment does not have an impact on child GPA. The 2SLS estimates are insignificant, and the coefficient of the OLS estimator even changes signs. At first sight these results deviate from the findings of Rege et al. (2011). Note, however, that, while I use grades in the same year as paternal unemployment, Rege et al. (2011) look at school grades around three years after paternal job loss.

Nevertheless, this result is striking because it indicates that paternal unemployment affects child upper secondary schooling decisions but not child school performance or abilities. In the context of the theoretical framework described in Section 3, this also indicates that paternal joblessness does not have an immediate effect on potential wages in either of the two education sectors, because wages are driven by child abilities and GPA is an indicator of ability and subsequent wages (Rose and Betts, 2004).

[22] For simulation results of the effect of labor market fluctuations see Web Appendix B.

[23] Estimates that restrict $\rho = 0$ are much lower in size than for the unrestricted model. Compare Table D.4.

[24] Again, a Durbin-Wu-Hausman test does not reject the H_0 of paternal unemployment being exogenous.

Table 8: Bivariate probit results of the effect of paternal unemployment on youth higher education decision

Upper secondary education	1	2	3	4	5
Schooling equation					
Father unemployed	-0.1899***	-0.1896***	-0.1836***	-0.1938***	-0.1852***
	(0.036)	(0.037)	(0.038)	(0.040)	(0.037)
Father grammar school	0.3245***	0.3253***	0.3050***	0.3098***	0.3209***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Father cognitive skills			0.07373***	0.07440***	
			(0.018)	(0.018)	
Paternal age	0.004277*	0.004277*	0.003641	0.002527	0.003294
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Unemployment equation					
Cyclical component of adult male unemployment	0.01130**	0.01130**	0.01077**	0.01283**	0.009684*
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Observations	2326	2326	2326	2326	2326
P-val LRtest of rho=0	0.48	0.52	0.94	0.01	0.50
Covariates included	YES	YES	YES	YES	YES
Labor market controls included	NO	YES	YES	YES	YES
Father cognitive Skills included	NO	NO	YES	YES	NO
Interaction effects	NO	NO	NO	YES	NO
Fixed Effects	state, time	state, time	state, time	state, time	region, time
Sample	All	All	All	All	All
log-lik	-1,900.67	-1,900.33	-1,870.71	-1,862.44	-1,785.39

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Standard errors clustered by region and bootstrapped using 200 replications. For all covariates included see Table 6.
Interaction effects are interactions between paternal education/cognitive ability/age and unemployment/local labor market variation, respectively. Biprobit coefficients displayed are average marginal effects for the probability Pr(Upper secondary education = 1) and Pr(Paternal unemployment = 1) (for regional unemployment variation) are reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.2 Heterogeneity of effects across different groups of individuals

For policy makers it is important to know which children are particularly vulnerable to paternal unemployment. This section first presents results generated by stratifying the sample on different parent and child characteristics. Then, I use my model results to show the degree of heterogeneity in the unemployment and labor market effects for fathers of different ages and cognitive abilities.

Regional labor market fluctuations only affect individuals who work in a respective region. Therefore, it is interesting to investigate this in order to see whether fathers who are willing to commute larger distances may be more likely to find a new job quickly and may be less affected by local labor market fluctuations. Column (1) of Table 10 indicates that the unemployment effect stays roughly constant after excluding those fathers from the sample

Table 9: The effect of paternal unemployment on youth GPA

GPA	2SLS		OLS
Treatment			
Father unemployed	4.1189	6.9192	-0.07813
	(3.287)	(5.995)	(0.073)
Vocational training positions per 100 applicants		0.05034	0.02031**
		(0.034)	(0.010)
Youth unemployment		-0.1298	-0.08605**
		(0.103)	(0.036)
Observations	2302	2302	2302
Covariates included	YES	YES	YES
Labor market controls included	NO	YES	YES
Father cognitive Skills			
P-val DWH-test (H0: unemp exogenous)	0.094	0.016	

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: For covariates included see Table 6.
GPA ranges from 6 (best grade) to 1 (worst grade).
German grades have been reversed.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

who commuted more than 30km to work in the past year. This effect may be caused by similar unemployment fluctuations in neighboring regions. Section 2.3 explained that schools in the German school system usually belong to one of three different tracks, where only the highest track provides automatic access to an upper secondary school degree. Hence, ex ante one may expect that paternal unemployment is more harmful for individuals with a lower track recommendation, who are more likely to attend the lower tracks where access to upper secondary schooling is not automatic. Columns (2) and (3) show that the marginal effect of paternal unemployment for individuals attending the highest school track is larger in absolute terms than for the middle track (recall that individuals of the lowest track are not part of the sample). However, note that the marginal effects are expressed in terms of percentage points. Regarding percentages the effect for individuals who had a low track recommendation (38 percent) is indeed significantly larger than for individuals with a high track recommendation (23 percent). Stratifying across gender in Columns (4) and (5) indicates that daughters are more prone to dropping out in response to paternal unemployment than boys. It may be that parents are more willing to cushion shocks towards their sons rather than daughters. What is also likely is that females lose confidence more easily in response to a family shock than boys. However, the difference in the effect between girls and boys is not significant. Due to institutional changes in the regulation and amount of unemployment benefits, unemployment hardship has increased in Germany from 2005 onwards. Hence, it is not surprising that the adverse effect of paternal unemployment is larger after the reform (Column (7)) than before

(Column (6)). Again, the difference in the effects between Column (6) and Column (7) is not significant.

In late 2008 the most recent economic crisis started and if the exclusion restriction is violated this is most likely the case for the crisis years when newspapers were full of bad news about the economy. Hence, in Column (8) I reestimate the model also for all years except the crisis years. Again, the point estimate is slightly larger but not significantly different from the point estimate in Column (1).[25]

6.3 The role of the subjective school success probability

In Section 3 I argued on theoretical grounds that the subjective school success probability is an important channel through which paternal unemployment affects child upper secondary school choices. For this to be true, three circumstances need to hold: First, paternal unemployment has to have a causal effect on the success probability. Second, the subjective probability of school success has to be a predictor for upper secondary school choice. Third, the fraction of the paternal unemployment effect explained by this probability has to be sufficiently large. This section will explore all three of these conditions in turn.

[25] Heterogeneity results for fathers with high/low cognitive ability, fathers with upper secondary schooling or below and fathers of different ages are displayed in Web Appendix C.

Table 10: Bivariate probit results of the effect of paternal unemployment on youth higher education decision, different subsamples

Upper secondary education	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Schooling equation								
Father unemployed	-0.1878***	-0.1921***	-0.1141***	-0.1551***	-0.2181***	-0.1819***	-0.2166***	-0.1976***
	(0.037)	(0.052)	(0.036)	(0.054)	(0.048)	(0.037)	(0.066)	(0.035)
Observations	1969	990	1336	1171	1155	1407	919	1856
P-val LRtest of rho=0	0.563	0.000	0.800	0.625	0.150	0.871	0.089	0.603
Covariates included	YES	YES	YES	YES	YES	YES	YES	YES
Labor market controls included	YES	YES	YES	YES	YES	YES	YES	YES
Fixed Effects	state, time	state, time	state, time	state, time	state, time	state, time	state, time	state, time
Sample	No commuters	High Track	Low track	Males	Females	<2005	>=2005	<2008
log-lik	-1,646.846	-520.285	-1,106.998	-946.777	-922.239	-1,149.317	-712.632	-1,529.312

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Standard errors clustered by region and bootstrapped using 200 replications.
For covariates included see Table 6.
Biprobit coefficients displayed are average marginal effects for the probability Pr(Upper secondary education = 1). Non-commuters are fathers who in (t-2) commuted less than 30km to work. High track denotes individuals who are in the highest secondary school track (Gymnasium). Low track are individuals in the low secondary school tracks, that is at schools which do not offer an upper secondary school degree (Hauptschule and Realschule).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I again use the cyclical component in an adult male unemployment as an instrumental variable for paternal unemployment to investigate the effect on the probability of school success and on the binary indicator $\mathbb{1}[Percentage > 50]$ using 2SLS and probit models respectively. Table 11 shows that the effect of paternal unemployment on that probability is significant and large in absolute terms. The estimate generated by the linear IV estimator in Column (1) indicates that the causal effect of paternal unemployment on the subjective school probability is a non-significant reduction of 11 percentage points of this probability. With a binary probit, I find that the probability of finding it rather likely to graduate is significantly reduced by 6.3 percentage points.

Table 11: The effect of paternal unemployment on the subjective probability of school success

Probability of school success	**2SLS**	**Biprobit**
Treatment		
Father unemployed	-11.109	-0.06333**
	(26.025)	(0.032)
Observations	2326	2326
P-val LRtest of rho=0		0.342
Covariates included	YES	YES
P-val DWH-test (H0: unemp exogenous)	0.784	

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: For covariates included see Table 6.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Except for the subjective school success probability, other child traits and preferences are also likely to be affected by paternal unemployment.[26] Table 12 displays the effect of paternal unemployment on child locus of control, child risk aversion and child mental health. The table shows that paternal unemployment reduces child mental health and child locus of control by a little over one standard deviation. The coefficient on risk aversion is positive but strongly insignificant.

After having shown that paternal unemployment has a large and significant negative effect on the subjective school success probability, I investigate whether that probability also has effects on child schooling decisions by including it as an additional covariate into the upper secondary school equation of Equation (5.1). The results are reported in Table 13. Column (1) includes the subjective school probability as a linear measure and Column (2) as a binary indicator for $\mathbb{1}[Percentage > 50]$. Only the marginal effect reported in Column (2) is significant and equals 0.07. Thus, if an individual thinks she is rather likely to succeed at school her probability to opt for upper secondary schooling increases by 7 percentage points.

[26]See Web Appendix A for an analysis of the effect of paternal unemployment on parental investments.

Table 12: Child preferences and traits through which paternal unemployment can affect youth higher education decisions (IV-2SLS estimator)

Child traits	**Mental Health**	**Risk aversion**	**Locus of control**
Treatment			
Father unemployed	-1.0312*	0.2146	-1.1190*
	(0.565)	(0.759)	(0.612)
Observations	2115	1909	2085
Covariates included	YES	YES	YES

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Standard errors clustered by region.
The analytical sample on which these estimates are based
consists of all GSOEP youths that have no missings in any of the covariates.
For covariates included see Table 6.
Trait measures are standardized with mean zero and standard deviation one.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The finding that only the the marginal effect in Column (2) is significant suggests that the effect of that probability is nonlinear and that individuals need to pass a certain threshold to choose higher schooling.[27]. This result is easily explained on hands of the model presented in Section 3. Departing from Equation (3.3), individuals will choose upper secondary education if it holds that

$$\sum_{t=t_e}^{T} \delta^t \mathrm{E}\big[w^1(t)\big] - \sum_{t=0}^{T} \delta^t \mathrm{E}\big[w^0(t)\big] > 0.$$

Solving this inequality for p gives:

$$p > \frac{\sum_{t=0}^{t_e} \delta^t w^l}{\sum_{t=t_e}^{T} \delta^t \left(w^h(t) - w^l(t)\right)} \tag{6.1}$$

$$p > \frac{\text{foregone earnings}}{\text{gain from education}}$$

Hence, the effect of the subjective probability in shifting an individual into upper secondary education is nonlinear. Individuals will choose upper secondary education only if that probability passes a certain threshold. Moreover, if individuals use the market interest rate to discount future earnings and have roughly equal wage streams in the two sectors, this threshold should be similar across individuals.

After having shown that paternal unemployment has a large and significant effect on the subjective school success probability and that this probability also affects upper secondary

[27] Robustness checks show that this threshold is somewhere between 50% and 60%. Unfortunately, the coding of the variable in steps of 10 does not allow a more precise analysis.

Table 13: Bivariate probit results of the effect of subjective school success on youth higher education decision

Upper secondary education	**1**	**2**
Probability, successful school completion	0.0001189	0.07259***
	(0.000)	(0.025)
Schooling equation		
Father unemployed	-0.1908***	-0.1862***
	(0.038)	(0.038)
Unemployment equation		
Cyclical component of adult male unemployment	0.01130**	0.01130**
	(0.005)	(0.005)
Observations	2326	2326
P-val LRtest of rho=0	0.522	0.604
Covariates included	YES	YES
Labor market controls included	YES	YES
Measure of school success probability	linear	binary (>50%)
Fixed Effects	state, time	state, time
Sample	All	All
log-lik	-1,900.296	-1,896.733

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Standard errors clustered by region and bootstrapped using 200 replications. For all covariates included see Table 6.
Biprobit coefficients displayed are marginal effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

school choice, it is interesting to see what part of the overall unemployment effect can be explained by that probability. I use the decomposition laid out in Section 5.4 and investigate how much of the difference in the unemployment effect can be ascribed to the probability that p is larger than 50 percent and to other child characteristics, after controlling for a large number of background variables.[28] Using the decomposition, paternal unemployment is estimated to reduce upper secondary schooling by 20 percentage points as can be seen from Table 14. Moreover, 2% of that reduction can be explained by the probability that p is larger than 50 percent. In Column (2) I add locus of control as an additional indicator of the school success probability. Hence, I make the assumption that locus of control is another measure of that same probability, because it evaluates whether an individual thinks that she can affect future wages by e.g. choosing education (Coleman and DeLeire, 2003). Doing so increases the explained part through upper secondary school success to 7.5 percent. Column (3) reveals that also adding mental health and risk aversion does further increase this explained part. Hence, both child mental health and risk aversion are not associated with a higher probability of upper secondary school choice.

[28] All background variables of Column 2 in Table 6 are included.

Table 14: Decomposition of the probability of child upper secondary education into subjective success probability, traits and background variables: fractions of overall effect ascribed to investments and parental background

Decomposition	(1)	(2)	(3)
SuccessProb	0.004177**	0.01445***	0.01559***
	(0.002)	(0.003)	(0.004)
Observations	1728	1728	1728
N(treated)	1,568.000	1,568.000	1,568.000
N(control)	160.000	160.000	160.000
Unemployment effect	0.201	0.206	0.206
%of unemployment effect explained by p	**2.081**	**7.019**	**7.553**
Variables included	Success prob	adding Loc	adding risk, mhealth

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Observations are weighted using coefficients of a pooled probit model.
Randomized ordering of variables used. Estimates based on 100 replications.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.4 Additional sensitivity analyses

In addition to the sensitivity analyses discussed so far, I have performed a range of further estimations to assess the robustness of the results with respect to the choice of covariates, outcome definition, coding the treatment and estimation strategy. First, much of my analysis hinges on the assumption that fluctuations in the regional unemployment rate only influence child schooling decisions via their effect on paternal unemployment. Admittedly, local labor market conditions may impact educational choices in ways that may not be transmitted solely through the father's unemployment experience. Regional fluctuations in GDP may also affect the general wage development in that region or a decline in tax revenue may affect school operations. Therefore, I conducted robustness checks where, in the first equation of the bivariate probit model, I also control for mean deviations in regional tax income and for mean deviations in the general wage development. Both of these variables do not affect my main coefficient estimates and do not significantly affect upper secondary school choice.

Second, I use a different coding of the outcome variable. While in my main estimations I use final level of schooling if observed and planned level of schooling if the final level is not yet observed, Table D.3 shows the main results of this analysis when using a binary indicator for whether an individual is still in school at age 17. In this case, the results are still significant, but the marginal effect size reduces by about 5 percentage points. I focus on final schooling for two reasons. First, an indicator for whether a child is still in school at age 17 is likely to be flawed for individuals who started school at a different age or had to repeat a grade. Second, final schooling is a much better predictor of later outcomes.

Third, I estimate the effect of involuntary unemployment instead of non-employment on child education decisions. The results are displayed in Table D.5, and the marginal effects obtained are extremely similar to the ones in Table 8.

Last, I use linear 2SLS-IV and OLS instead of nonlinear probit estimators. Using 2SLS entails considerable increase in effect sizes as can be seen in Table D.2. Note that the IV-estimator provides a weighted local average treatment effect for children of fathers who are shifted into unemployment due to a regional labor market downturn, while the bivariate probit results are average marginal effects. Hence, a straightforward explanation for the larger effect size is treatment heterogeneity and that children of individuals affected by a regional downturn (*compliers*) are worse off when compared to children of individuals who do not experience a change in employment in times of recession (*never-takers* and *always-takers*).[29]

7 Conclusion

This paper shows that paternal unemployment has a large and significant effect on child upper secondary school choice and that the subjective probability of successful school completion is a driving mechanism behind this effect. Moreover, the study identifies heterogeneity in the paternal unemployment effect for different groups of children and fathers. I estimate a simultaneous equation latent variable model for the joint probability of child upper secondary school choice and paternal unemployment using regional variation in the cyclical component of adult male unemployment in the labor market of the father as an exogenous shifter for paternal unemployment. To interpret my findings and to link them to the theory of human capital investment decisions, I present a simple theoretical framework that explains how paternal unemployment affects schooling decisions by means of the perceived school success probability. Within this framework, young individuals make upper secondary schooling decisions by comparing discounted expected wage flows for each schooling choice.

Paternal unemployment reduces the probability of upper secondary school choice by roughly 18 percentage points or 34 percent. Paternal unemployment reduces the probability that an individual finds it rather likely that she will graduate successfully by 7 percentage points. It also reduces child locus of control and child mental health by roughly one standard deviation. The theoretical framework that motivates my analysis predicts that the subjective school success probability has a nonlinear effect on child upper secondary school choice, and the

[29] 2SLS is also biased in small samples, such that part of the increase may be ascribed to that bias (Chiburis et al., 2012).

empirical analysis confirms this presumption. Overall, the subjective school success probability explains about 2-7.5 percent of the overall gap in different upper secondary school choice probabilities between employed and unemployed fathers.

Some of the results are specific to the German institutional system. First, in percentage terms, children who visit schools of the lower secondary school tracks are more affected from paternal unemployment than children who visit higher-track schools. Second, unemployment has a more detrimental effect after a substantive reform of the unemployment benefit system as of January 2005, the so-called Hartz IV reform, although the difference is not significant.

Given the finding that regional labor market downturns are an important driver of child education decisions via their effect on paternal unemployment, this paper contributes to the discussion on second order effects of economic crises. Using the structure of my model to predict the effect of a recession on the marginal probability of upper secondary school choice, I find that a labor market downturn that is similar in size to that in the US during the Great Recession leads to a reduction in the upper secondary school choice probability by 2 percentage points.

My finding that paternal unemployment has adverse effects on child outcomes confirms earlier findings by Rege et al. (2011), Oreopoulos et al. (2008), Kalil and Ziol-Guest (2008) as well as Stevens and Schaller (2011). Yet, the paper differs substantially from these other studies in the literature focusing primarily on the psychological and behavioral impacts of paternal unemployment on the child rather than on paternal investments.[30] The children of unemployed fathers in this study are substantially older than in any of the above-named papers. At age 16, cognitive skill production is largely completed which explains why in contrast to **?** I find that child GPA is not affected by paternal unemployment.

This paper shows that economic crises can have very important second order effects in terms of education outcomes of the next generation. From a policy perspective, this is relevant because it shows that part of the negative effect of paternal unemployment on education decisions can be mitigated by policy interventions focused on changing self-confidence and expectations about the future. Such policies are likely to be more cost-effective than seeking to directly improve cognitive abilities. Arguably, this paper is limited in scope. First, it focuses on teenage children only, and second it only investigates the impact of paternal unemployment on child secondary school choice. The present study may, therefore, be seen

[30]Results for the effect of paternal unemployment on parental investment patterns are presented in Web Appendix A.

as a motivation to construct models, which allow for different channels and mechanisms linking familial distress to human capital investment decisions.

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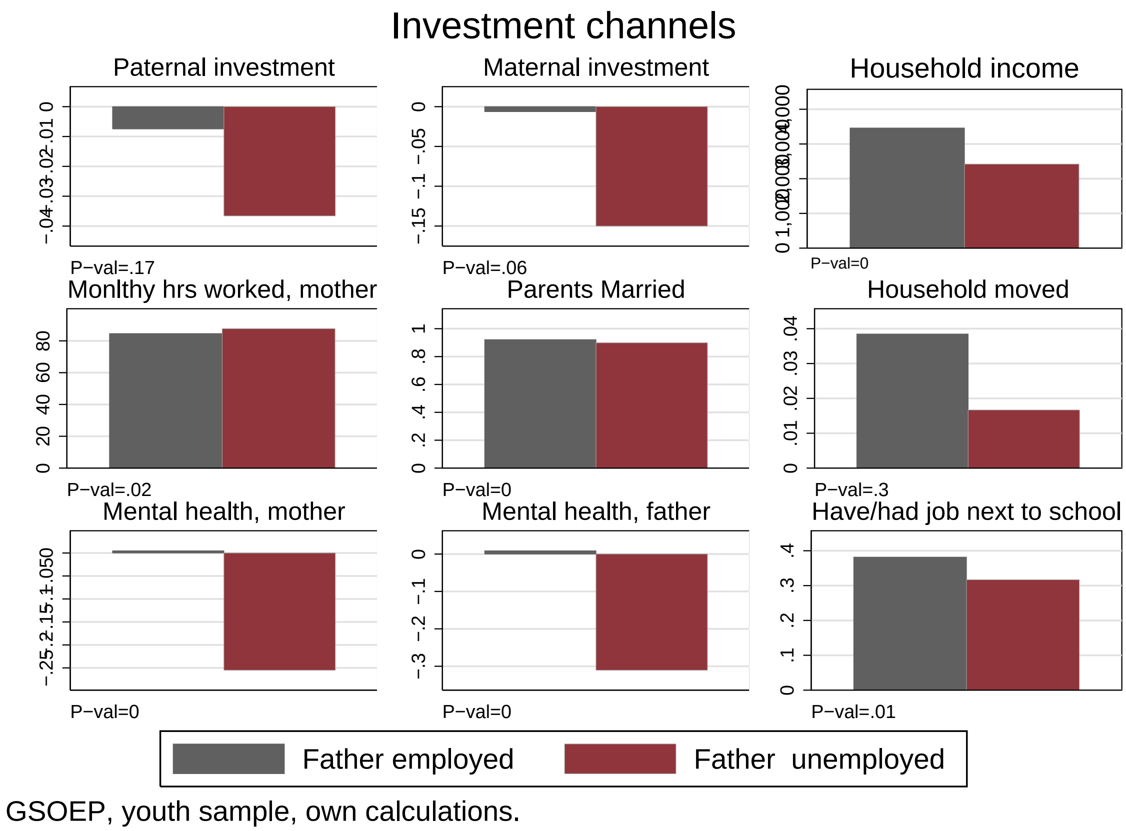
Appendix A The effect of paternal unemployment on parental investments

Figure A.1: Parental investments by paternal unemployment status



Notes: GSOEP youth sample 2000-2010.

The finding that background characteristics are much more important than income is consistent with the findings of Blau (1999).

Table A.1: Investment channels through which paternal unemployment can affect youth higher education decisions

Parental investments	**HH income**	**Mother work hrs**	**Par married**	**HH moved**	**paternal inv**	**maternal inv**	**paternal MH**	**maternal MH**	**Youth job**
Father unemployed	-0.7727**	29.111	-0.2104	0.01346	-0.5645	-1.3297	-1.8351*	-0.2241	-0.5323
	(0.344)	(60.010)	(0.260)	(0.173)	(1.049)	(1.093)	(1.051)	(0.998)	(0.491)
Observations	2126	2263	2220	2263	2029	1993	2263	2219	2263
Covariates included	YES	YES	YES	YES	YES	YES	YES	YES	YES
Regional controls included	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Standard errors clustered by region. The analytical sample on which these estimates are based consists of all GSOEP youths that have no missings in any of the covariates. For covariates included see Table 6.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Detailed decomposition of the probability of child upper secondary education into parental investments and background variables: Fractions of overall effect ascribed to investments and parental background

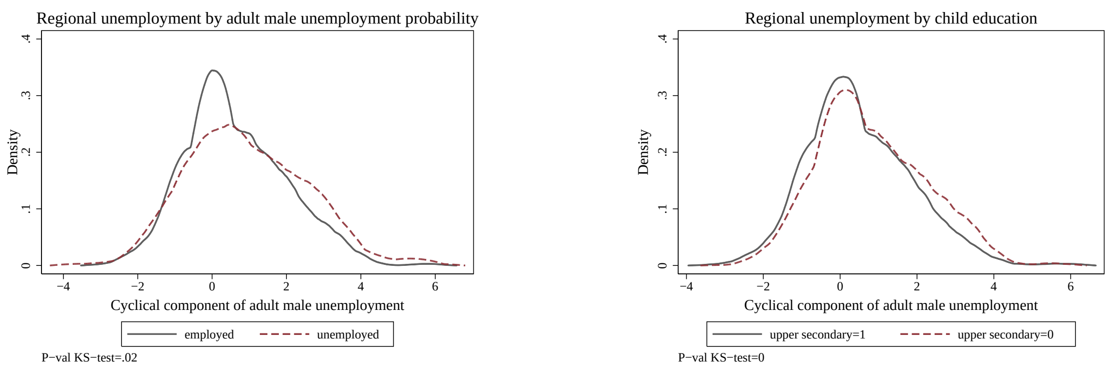
Decomposition, detailed	**(1)**	**(2)**
Background	0.1223***	0.1403***
	(0.014)	(0.013)
Investments		
Log HH-income	0.05591***	
	(0.015)	
Monlthy hrs worked, mother	-0.001970	-0.0002950
	(0.002)	(0.002)
Parents Married	0.0006326	0.002721
	(0.002)	(0.002)
Household moved	0.0009690	0.001384
	(0.002)	(0.002)
Paternal investment	0.01632***	0.01605***
	(0.005)	(0.004)
Maternal investment	-0.0004967	-0.0003147
	(0.004)	(0.004)
Mental health, father	-0.002660	-0.0008301
	(0.005)	(0.005)
Mental health, mother	0.006527*	0.008134**
	(0.003)	(0.004)
Have/had job next to school	0.004403	0.004155*
	(0.003)	(0.002)
Observations	1531	1531
N(treated)	1,392.000	1,392.000
N(control)	139.000	139.000
Pr(S=1—U=1)	0.571	0.571
Pr(S=1—U=0)	0.230	0.230
Difference	0.341	0.341
Total explained	0.204	0.172
Variables included	all	excl HH-income

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Observations are weighted using coefficients of a pooled probit model.
Randomized ordering of variables used. Estimates based on 100 decomposition replications
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B The effect of labor market fluctuations

I also consider the impact of regional labor market downturns. Figure B.1 displays the association between regional unemployment deviations and unemployment or education by showing kernel densities of the cyclical component of adult male unemployment by education and employment, respectively. Unsurprisingly, densities for unemployed fathers and children without upper secondary schooling are shifted to the right. The overall effect of fluctuations in the cyclical unemployment component as predicted from the model can be seen in Figure B.2. The gradient of the line shows the degree to which regional unemployment influences child upper secondary schooling decisions via the effect on paternal unemployment. Note that this gradient is surprisingly steep indicating that economic crises have considerable second order effects on next generation schooling choices.

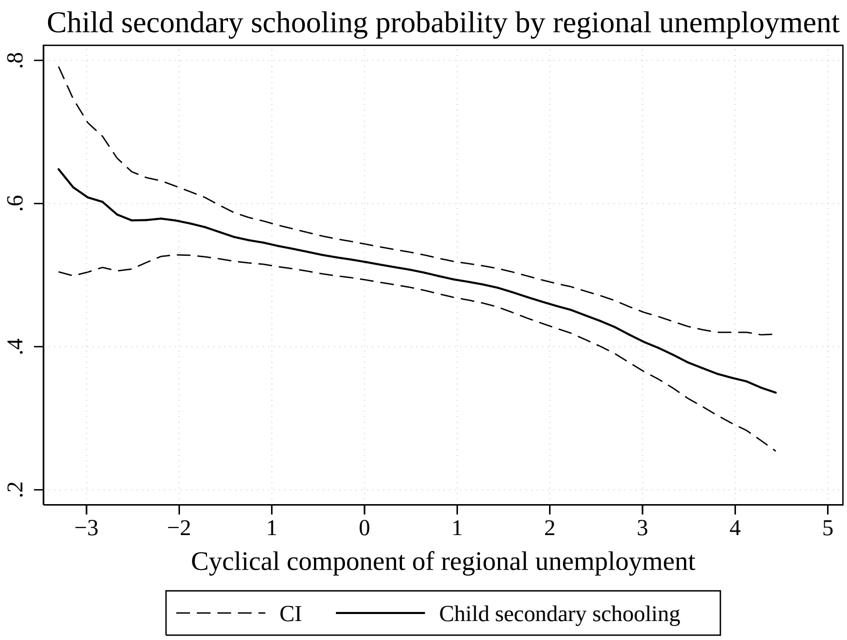
Figure B.1: Cyclical component of adult male unemployment by paternal unemployment and youth upper secondary education.



(a) Paternal unemployment **(b)** Youth higher education

Notes: Model simulation results. Estimates of model (4) in Table 8. Kernel density estimation implemented using a Gaussian kernel with bandwidth selected using Silverman's rule of thumb (Silverman, 1986). Kolmogorov-Smirnov test: Two-sample KS-test with null hypothesis that the two distributions are the same. p-values reported underneath graphs.

Figure B.2: Effect of cyclical unemployment fluctuations in paternal labor market on youth upper secondary schooling.

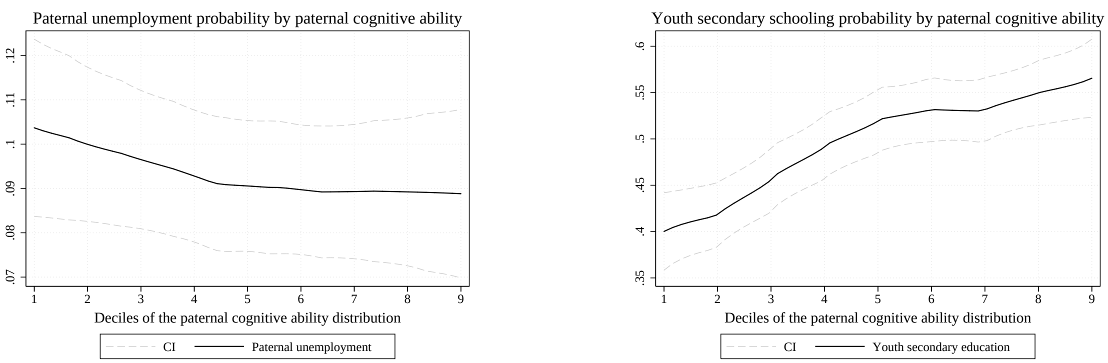


Notes: Model simulation results. Simulation based on estimates of model (4) in Table 8. 95% pointwise confidence interval between dashed lines.

Appendix C The Role of Paternal Characteristics

The analysis in the main part of the paper investigates average marginal effects for different models and different strata of the sample. Model (4) contains interaction effects for different paternal characteristics, which are important when thinking about the intergenerational transmission of disadvantage in response to labor market shocks. When using interaction terms in nonlinear models, coefficients are hard to interpret. Therefore, I use the structure of the model and the interaction terms to predict probabilities for three different groups of fathers: Fathers with high/low cognitive ability, fathers with upper secondary schooling or below and fathers of different ages.[31] The main prediction results are based on coefficients of model (4) in Table 8. Figure C.1 and Figure C.2 show the predicted unemployment and education probabilities for fathers with different cognitive abilities and ages. Even after conditioning on schooling, higher paternal cognitive skills significantly reduce the unemployment probability and significantly increase the probability of child upper secondary schooling.

Figure C.1: Effect of paternal cognitive ability (after conditioning on education) on paternal unemployment and youth upper secondary education.



(a) Paternal unemployment **(b)** Youth higher education

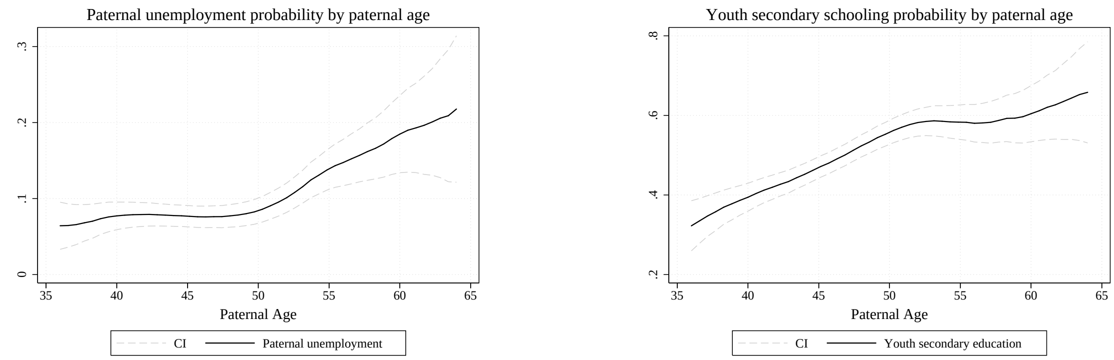
Notes: Model simulation results. Simulations based on estimates of model (4) in Table 8. 95% pointwise confidence interval between dashed lines.

If a father could be moved from the lowest to the highest decile of the cognitive ability distribution, his child would be 15 percentage points more likely to choose upper secondary schooling. Paternal age also has a positive effect on child schooling decisions but a negative effect on the employment probability. Unsurprisingly, Figure C.3 shows that individuals with upper secondary schooling are less likely to become unemployed while their children are more likely to choose upper secondary education.

Figure C.4 investigates the overall effect of paternal unemployment for fathers with high/low cognitive abilities, with high and low education levels and with different ages. For each of these graphs, a move along the x-axis leads to a widening in the difference of upper secondary school probabilities between employed and unemployed fathers. Hence, the effect of unemployment tends to be somewhat more detrimental for fathers with high cognitive abilities, high education and higher age. This seems surprising at first, given that families

[31] Goodness-of-fit statistics for using the model to predict outcomes are presented in Table D.6.

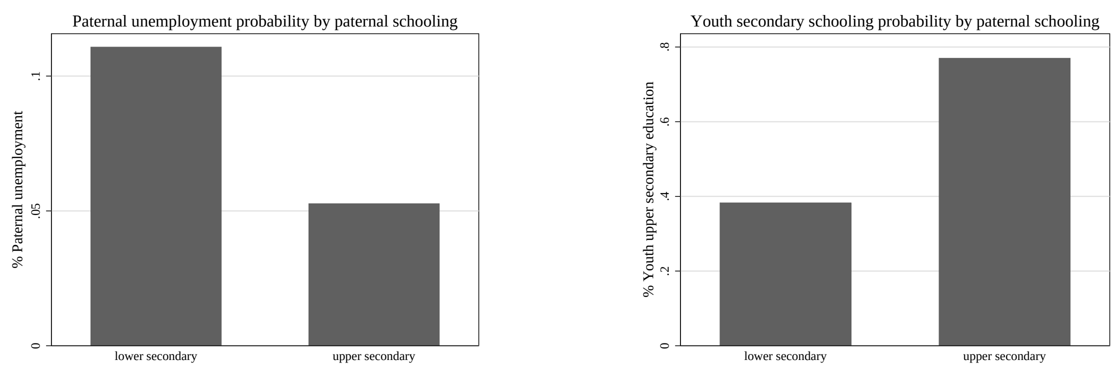
Figure C.2: Effect of paternal age on paternal unemployment and youth upper secondary education.



(a) Paternal unemployment **(b)** Youth higher education

Notes: Model simulation results. Simulations based on estimates of model (4) in Table 8. 95% pointwise confidence interval between dashed lines.

Figure C.3: Effect of paternal upper secondary education on paternal unemployment and youth upper secondary education.



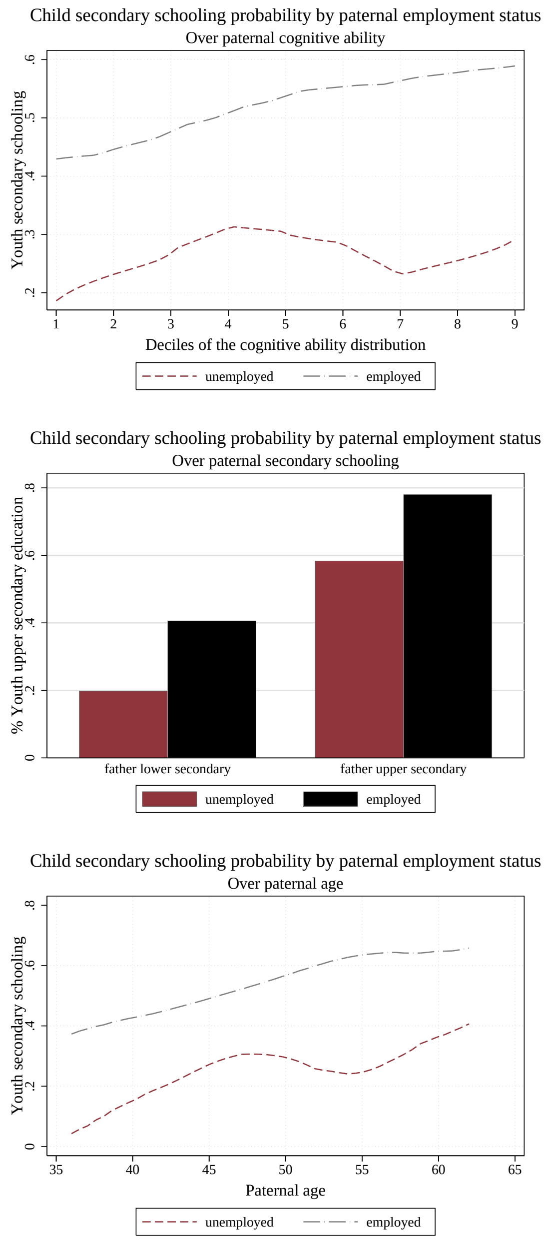
(a) Paternal unemployment **(b)** Youth higher education

Notes: Model simulation results. Simulations based on estimates of model (4) in Table 8.

with higher ability endowments should be able to cushion shocks more easily. However, at the same time, the graphs display the average treatment effect of individuals with different endowments. Hence, given that the event of unemployment is very unlikely for fathers with high cognitive abilities, it may simultaneously be psychologically more detrimental to these individuals.

I also use the model to predict the effects of a recession where unemployment increases in all regions by 4 percentage points. This is about the effect that the most recent crisis had on US unemployment rates. When predicting probability of upper secondary school success for different levels in regional unemployment rates, I find that overall there is not much heterogeneity in the response of child upper secondary schooling to regional labor market downturns for fathers with different characteristics. Panel 1 of Figure C.5 shows that children

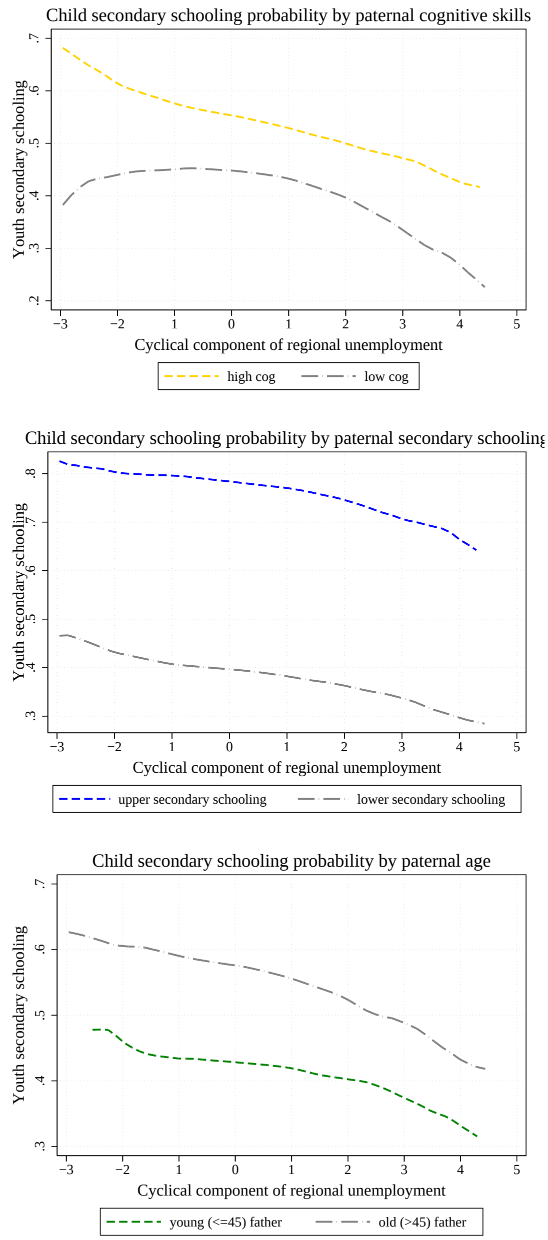
Figure C.4: Heterogenous effect of paternal unemployment on child upper secondary schooling by paternal cognitive ability, education and age



Notes: Model simulation results. Simulation based on estimates of model (4) in Table 8.

of fathers with an upper secondary school degree suffer slightly more from a regional labor market downturn than children from fathers with lower education. Moreover, children of older fathers are slightly less affected by labor market downturns (Panel 3 of Figure C.5).

Figure C.5: Heterogenous effect of regional cyclical unemployment fluctuations on child upper secondary schooling by paternal cognitive ability, education and age



Notes: Model simulation results. Simulation based on estimates of model (4) in Table 8.

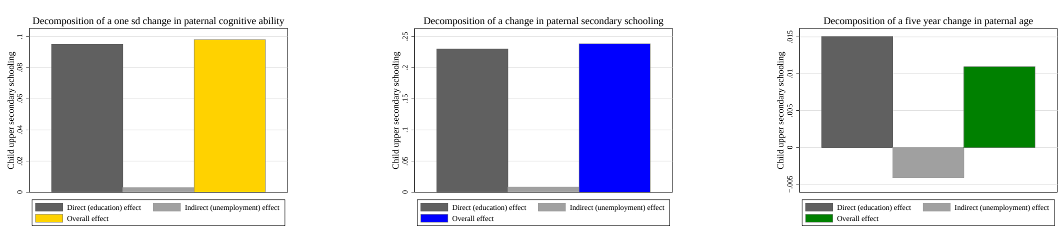
C.1 Direct, indirect and total effects of paternal characteristics

From a policy perspective, it is interesting to see how the effect of regional labor market downturns and paternal unemployment varies for fathers with different observable characteristics. Different paternal characteristics may affect the probability to choose upper secondary schooling either directly or because they affect the probability of paternal unemployment. The total effect of a paternal characteristic c^j can be decomposed into a direct and an indirect effect according to:

$$
\begin{aligned}
&\overbrace{\frac{dP\left(S=1|X=x\right)}{dc^j}}^{\text{Total effect}} \\
= \;& \overbrace{\sum_{D=0}^{1} P(D=d|X=x, C^j=c^j)\frac{\partial P(S=s|X=x, C^j=c^j, D=d)}{\partial c^j}}^{\text{direct effect}} \\
+ \;& \overbrace{\sum_{D=0}^{1} \frac{\partial P(D=d|X=x, C^j=c^j)}{\partial c^j} P(S=s|X=x, D=d, C^j=c^j)}^{\text{indirect effect}}
\end{aligned}
$$

The indirect effect represents a reduced probability to opt for upper secondary schooling induced by a change in the probability of paternal unemployment, which is induced by a change in the respective paternal characteristic. The direct effect is the part of the effect of a characteristic that is unrelated to unemployment and directly influences the education probability. The results of the decomposition of Section C.1 are displayed in Figure C.6. The graphs show that paternal cognitive abilities and paternal education have large positive direct effects on child upper secondary schooling. The effect of paternal age, on the other hand, is very small. Moreover, the indirect effect of paternal age is negative because higher paternal age leads to a reduction in the employment probability.

Figure C.6: Decomposing the effect of a change in paternal cognitive ability, schooling and age on child upper secondary schooling decisions.



Notes: Model simulation results. Simulation based on estimates of model (4) in Table 8.

Appendix D Additional Tables

Table D.1: Raw correlation: paternal/maternal change to non(un-)employment and gpa

Newly unemployed	**GPA**
Father becomes unemployed	-0.06062
	(0.113)
Father becomes involuntarily unemployed	-0.08875
	(0.126)
Mother becomes unemployed	0.07079
	(0.127)
Mother becomes involuntarily unemployed	-0.06773
	(0.141)
Observations	2098 (father) 2071 (mother)
Covariates included	NO
R-squ adj.	-0.00

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Standard errors are robust.
Raw correlations displayed, no covariates included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.2: 2SLS/OLS-results of the effect of paternal unemployment on youth higher education decision

Upper secondary education	2SLS	2SLS	2SLS	OLS
Treatment				
Father unemployed	-0.5479**	-0.6279**	-0.5224**	-0.1951***
	(0.263)	(0.245)	(0.264)	(0.032)
Vocational training positions per 100 applicants			-0.003490	-0.004321
			(0.004)	(0.003)
Youth unemployment			-0.01381	-0.02057*
			(0.011)	(0.012)
Father cognitive skills		0.08385***	0.08522***	0.09054***
		(0.017)	(0.017)	(0.010)
Observations	2326	2326	2326	2326
Covariates included	YES	YES	YES	YES
Labor market controls included	NO	NO	YES	YES
Father cognitive Skills	NO	YES	YES	YES
R-squ adj.	0.160	0.165	0.191	0.226
P-val DWH-test (H0: unemp exogenous)	0.198	0.074	0.197	

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: For covariates included see Table 6.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.3: Using higher secondary school at age 17 as outcome variable instead of final schooling

Upper secondary education (at 17)	**1**	**2**	**3**	**4**	**5**	**6**
Treatment						
Father unemployed	-0.1340***	-0.1051***	-0.09708*	-0.03441	-0.08829	-0.1413***
	(0.036)	(0.039)	(0.057)	(0.030)	(0.062)	(0.051)
Vocational training positions per 100 applicants	0.001466	0.0007131	0.1585	-0.002730	0.004609	-0.001726
	(0.004)	(0.005)	(0.099)	(0.004)	(0.007)	(0.006)
Youth unemployment	-0.002948	-0.01312	0.003744	-0.01320	0.002544	0.02961
	(0.015)	(0.016)	(0.006)	(0.017)	(0.025)	(0.034)
Father cognitive skills	0.04713***	0.04777***	-0.007381	0.03067*	0.06477***	0.03160*
	(0.015)	(0.016)	(0.024)	(0.016)	(0.018)	(0.019)
Observations	2326	1969	990	1336	1171	1155
P-val LRtest of rho=0	0.419	0.743	0.715	0.257	0.272	0.578
Covariates included	YES	YES	YES	YES	YES	YES
Labor market controls included	YES	YES	YES	YES	YES	YES
Father cognitive Skills	YES	YES	YES	YES	YES	YES
Sample	All	No commuters	High Track	Low track	Males	Females
log-lik	-1,881.471	-1,625.069	-601.984	-926.557	-894.890	-947.155

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Standard errors clustered by region and bootstrapped using 500 replications.
For covariates included see Table 6.
Biprobit coefficients displayed are average marginal effects for the conditional probability Pr(Upper secondary education = 1).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.4: Binary probit results, $\rho > 0$

Upper secondary education	**1**	**2**
Treatment		
Father unemployed	-0.2965**	-0.3011*
	(0.136)	(0.158)
Observations	2326	2326
P-val LRtest of rho=0	0.475	0.499
Covariates included	YES	YES
Labor market controls included	NO	YES
Sample	All	All
log-lik	-1,785.556	-1,785.058

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Standard errors clustered by region.
For covariates included see Table 6.
Biprobit coefficients displayed are average marginal effects for the conditional probability Pr(Upper secondary education = 1).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.5: Binary probit results using involuntary unemployment instead of unemployment as treatment variable

Upper secondary education	1	2
Schooling equation		
Father unemployed, actively looking	-0.1899***	-0.1896***
	(0.036)	(0.037)
Observations	2326	2326
P-val LRtest of rho=0	0.160	0.619
Covariates included	YES	YES
Labor market controls included	NO	YES
Sample	All	All
log-lik	-1,717.647	-1,717.303

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Standard errors clustered by region and bootstrapped using 200 replications. For all covariates included see Table 6.
Interaction effects are interactions between paternal education/cognitive ability/age and unemployment/local labor market variation, respectively. Biprobit coefficients displayed are average marginal effects for the probability Pr(Upper secondary education = 1) and Pr(Paternal unemployment = 1) (for regional unemployment variation) are reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.6: Model simulation, goodness-of-fit statistics

	Predicted	Actual	Difference	goodness-of-fit P-val chi2	Pct corr pred
Unemployment	.0937	.0967	-.003	0	.8491
Child upper secondary education	.4966	.5181	-.0215	0	.6028

Note: Statistics for simulation of model (4) in Table 8 shown.

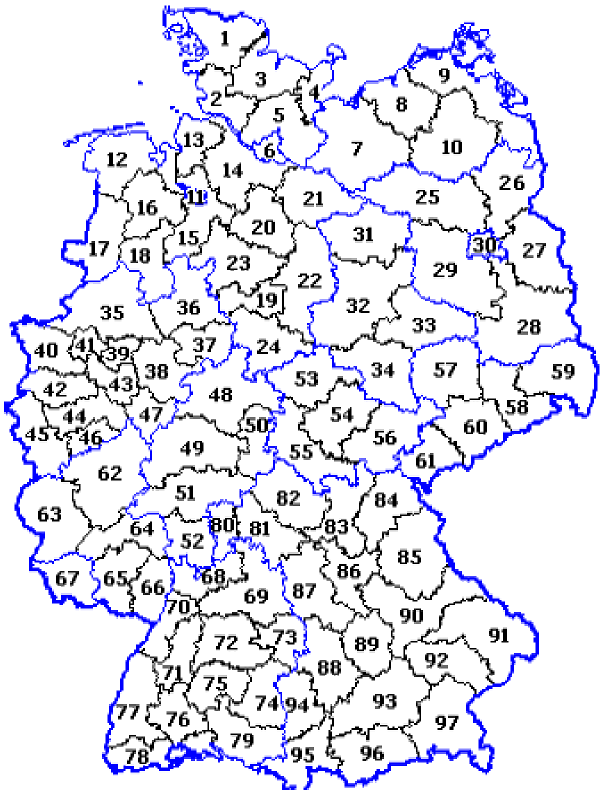
Table D.7: Probit model results for the probability of child upper secondary education on child traits

Probit base for composition	(1)	(2)	(3)	(4)
Success Probability				
Probability, successful school completion > 50%	0.1036***	0.08325**	0.06852**	0.08247**
	(0.036)	(0.032)	(0.032)	(0.033)
Traits				
Youth mental health			-0.004553	0.003031
			(0.011)	(0.011)
Youth risk aversion			0.002757	-0.0003157
			(0.011)	(0.011)
Youth locus of control			0.04711***	
			(0.011)	
Observations	1728	1728	1728	1728
R-squared adj.	0.003	0.200	0.207	0.200
Variables included	all	all	all	excl Locus
Background variables included	YES	YES	YES	YES

Standard errors in parentheses
Source: GSOEP Youth Sample.
Note: Model serves as a basis for the decompositions displayed in Table 14 and Table A.2. Average marginal effects reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

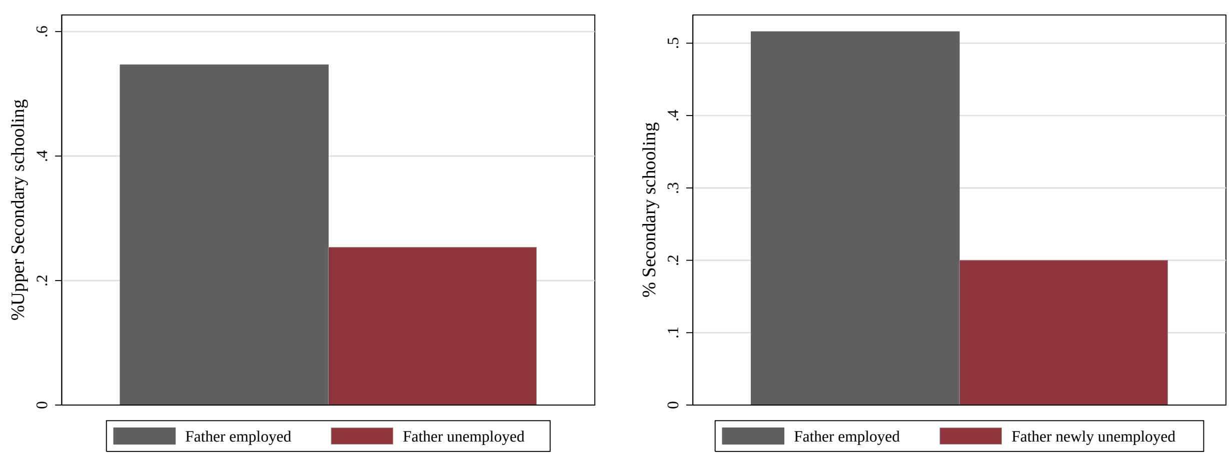
Appendix E Additional graphs

Figure E.1: Labor market regions



Source: Regional statistics, German employment agency

Figure E.2: % higher education paternal unemployment status and by whether the father is newly unemployed (employed last period, unemployed this period).

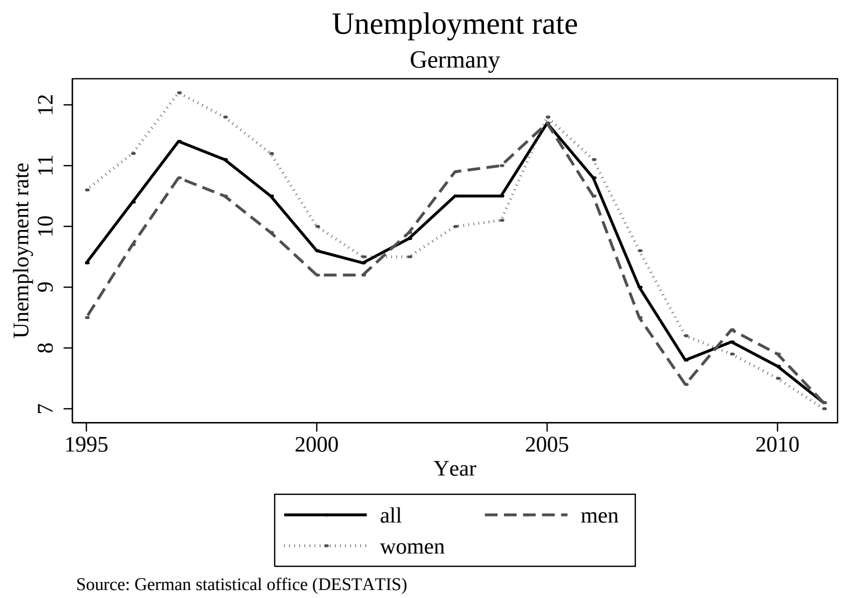


(a) Upper secondary schooling by paternal unemployment

(b) Upper secondary schooling by newly unemployed

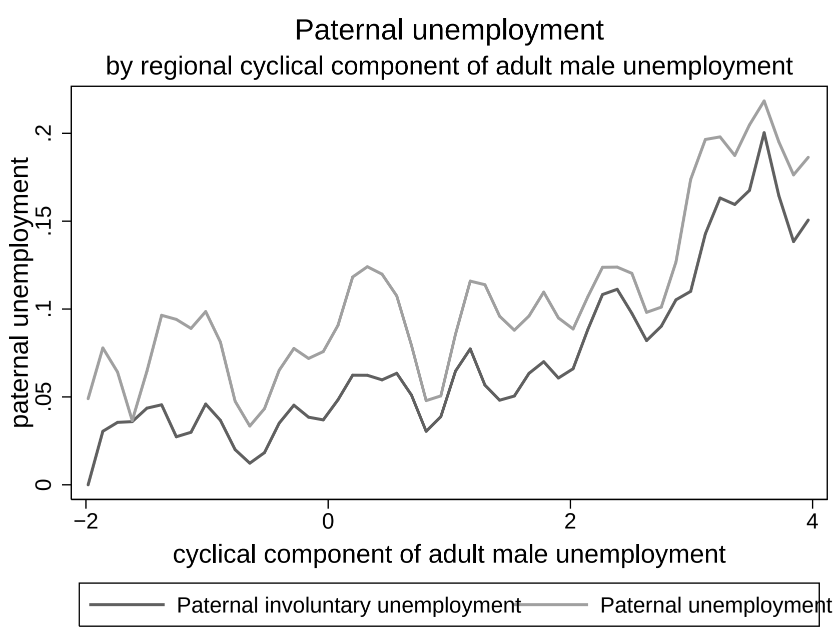
SOURCE: SOEP, youth dataset (2000-2010).

Figure E.3: Unemployment rate, Germany 1995-2011



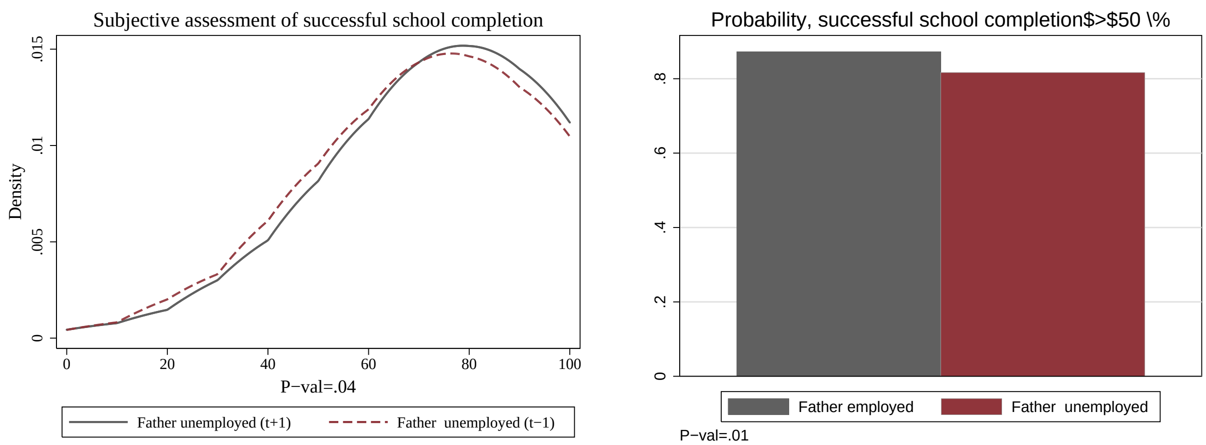
Source: German statistical agency (DESTATIS)

Figure E.4: Paternal unemployment by regional cyclical component of adult male unemployment, strong undersmoothing.



Notes: Graphs display kernel-weighted local polynomial regression outputs of paternal unemployment on the regional component of adult male unemployment. Smoothing is obtained from Epanechnikov Kernel weighted local polynomial estimates. Strong undersmoothing used to show co-movement of the two measures of paternal unemployment.

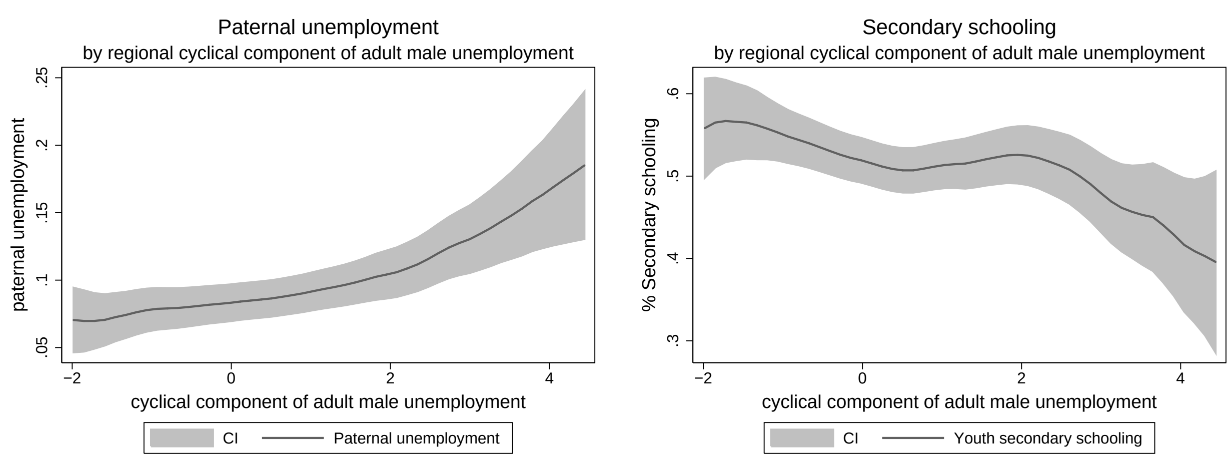
Figure E.5: Difference in subjective probability of successful school completion.



(a) Probability of success **(b)** Probability of success > 50%

Notes: GSOEP youth sample 2000-2010. P-value for (a) a Kolmogorov-Smirnov test for the equality of distribution and (b) for a Pearson's Chi-square test for equal frequencies reported.

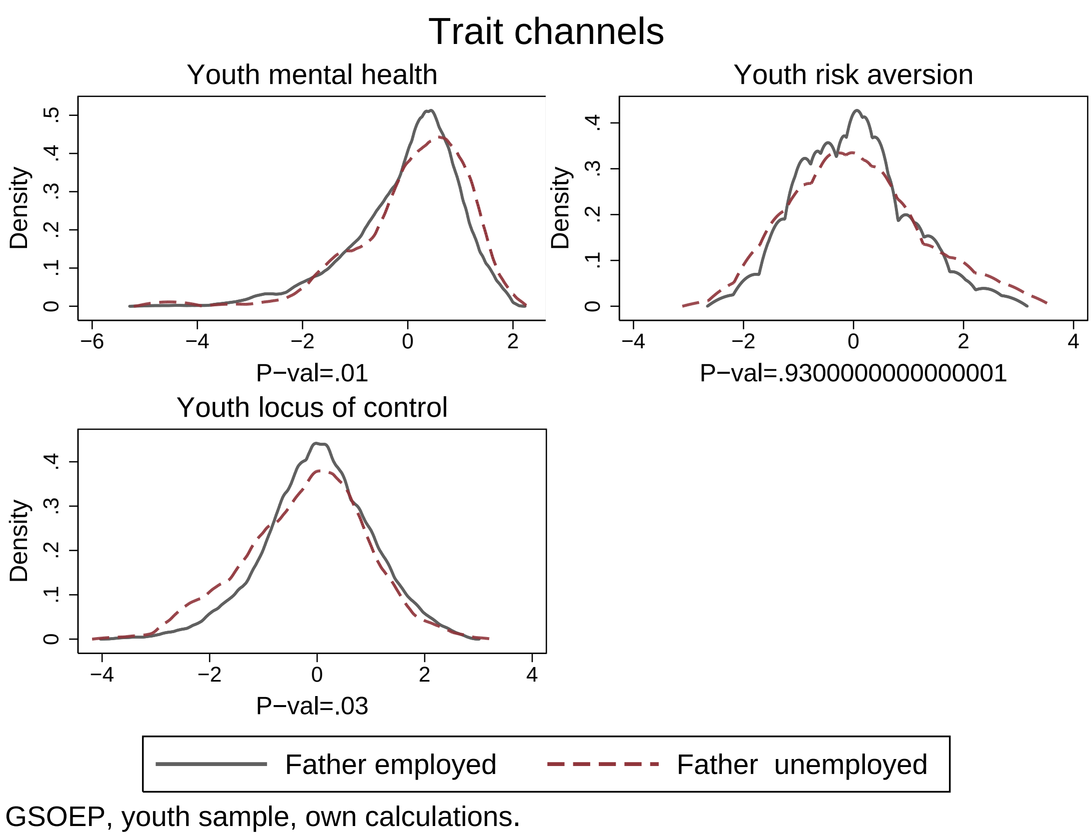
Figure E.6: Paternal unemployment and youth upper secondary schooling by regional cyclical component of adult male unemployment.



(a) Paternal unemployment **(b)** Youth upper secondary schooling

Notes: Graphs display kernel-weighted local polynomial regression outputs of paternal unemployment on the regional component of adult male unemployment. Smoothing is obtained from Epanechnikov Kernel weighted local polynomial estimates. Bandwidth selection follows Silverman's rule of thumb (Silverman, 1986). Shaded area displays 95% confidence bands.

Figure E.7: Youth trait measures by paternal unemployment status



Notes: GSOEP youth sample 2000-2010. P-value for a Kolmogorov-Smirnov test for the equality of distribution reported.