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Abstract

This paper analyses the role of family risk attitudes in intergenerational mobility in incomes and education. Based on 1984-2009 data of sons and fathers from the German Socio-Economic Panel Survey, there is evidence suggesting that sons with risk *taking* fathers have a significantly higher educational mobility and persistently higher income mobility than peers with risk *averse* fathers. They obtain significantly higher levels of education, which would be justified by modest evidence on higher returns to education.

The relationship seems more complex for sons' own risk attitudes. Risk *taking* sons experience higher educational mobility, but there is no difference in income mobility to risk *averse* sons. There are no considerable differences in the levels of education, but modest evidence suggesting lower returns to education for risk *taking* sons.

The findings improve the understanding of the intergenerational transmission mechanism of economic status and show that family risk attitudes impact economic mobility. The study suggests an important intergenerational link between fathers' risk attitudes and sons' levels of education, which has not received much attention in the literature.

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1 Introduction

Regardless of the socio-economic background of individuals, mere effort and personal ability level the ground for economic success in equal opportunity societies. This is widely perceived as desirable goal of social policy making in developed countries.

Economists attempt to measure the extent to which societies provide this equality of opportunity by the degree of persistence in economic status across family generations. Previous research found considerable correlations between the economic status of parents and their children, raising doubts about the real meritocracy of societies. This intergenerational dependence also closely links to economic inequality. Economic mobility is seen as a condition for a long-term balancing in the income distribution. Where mobility is restricted, the degree and persistence of inequality is more pronounced (e.g. Shorrocks, 1978, Atkinson, 1981).

Since the pioneering work of the British scientist Francis Galton (1889), who studied the intergenerational correlation of body heights, there is a long-lasting interest in intergenerational correlations of individual characteristics, which can be formalised by the simple regression model

$$y_{1j} = \alpha + \beta y_{0j} + \varepsilon_{1j}$$

with y_{1j} and y_{0j} denoting individual characteristics in the offspring and parental generation (Solon, 1999). The coefficient β measures the degree of intergenerational association of characteristics, where a high value represents a strong association. Economists' interest has focused on the transmission of economic status, especially occupations, incomes, wealth and education. While the early literature focused on the correct measurement of these similarities, the last decade of research has concentrated on understanding determinants and the underlying transmission mechanism, which is far from being well-understood. Recent research studies the transmission of personal traits and attitudes and their role in the intergenerational transmission of economic status. Black *et al.* (2009) demonstrated a considerable similarity of cognitive ability between generations. Blanden *et al.* (2007) found this ability to impact educational attainments, which in turn mediate the transmission of economic status.

The purpose of this study is to further enhance the understanding of the transmission mechanism. Dohmen *et al.* (2006) provide evidence on the transmission of personal risk attitudes between parents and their children. As these attitudes are interfering with many economic decisions, they are suspected to have an important impact on the intergenerational transmission of economic status.

This paper studies the role of children's and their parents' risk attitudes in income mobility and educational mobility. As previous research assigned an important role to education in the transmission process, I further examine how these family risk attitudes impact children's educational attainments, hypothesising an important role for parental risk attitudes.

The analysis is based on 1984-2009 data for fathers and sons from the German Socio-Economic Panel Survey. It provides a wide range of socio-economic information on individuals and allows for the required matching of fathers and sons. In 2004, the panel conducted an additional survey on individual risk attitudes, which was experimentally confirmed to be a valid predictor of decisions involving risk (Dohmen *et al.*, 2005). This builds an appropriate ground to approach the research questions.

Risk *taking* sons do not appear to have higher income mobility than risk *averse* sons, though they exhibit significantly higher educational mobility. Contrary to theory, sons' risk attitudes do not exhibit direct links to their education levels. Weak evidence suggests them to earn lower returns to education than risk averse sons.

For sons of risk *taking* fathers, the analysis identifies persistent signs of higher income mobility, a significantly higher educational mobility and higher levels of education. Modest evidence of higher returns to education supports the latter finding.

So far, the mostly theoretical consensus assigns an important role to individuals' own risk attitudes in the human capital investments process (e.g. Becker, 1993). I identify a largely unstudied link between offspring education levels and parental risk attitudes and confirm pioneering findings by Brown *et al.* (2012) who suggest a positive relation between children's levels of education and parents' willingness to take risk. The result adds to the understanding of the intergenerational transmission of incomes and is also interesting in guiding public policy on equality of opportunity.

The remainder of this study is organised as follows. Section 2 provides an overview of the development of the intergenerational mobility literature and recent advances in the understanding of the transmission mechanism. Section 3 states the research hypotheses and describes the econometric strategy. Section 4 describes the data, key variables and basic statistical relationships. Section 5 summarises the empirical findings which are discussed in section 6. Section 7 concludes.

2 Literature review

2.1 Intergenerational associations

Research in the field of intergenerational mobility analyses the transmission of economic status from parents to their children. The classical statistical model is

$$y_{Sj} = \alpha + \beta y_{Fj} + \varepsilon_{Sj} \tag{1}$$

with y_{Sj} and y_{Fj} denoting the log income of offspring S and parent F in family j, respectively. This leads to an interpretation of β as the intergenerational earnings elasticity (IGE). Higher values of β represent stronger associations of incomes between generations. With $\beta = 1$, lifetime incomes exhibit a perfect positive statistical association and society is completely immobile. Accordingly, $\beta = 0$ implies no statistical association between generations' incomes and complete mobility (Solon, 1999).[1] There is no philosophy or societal agreement on β-values indicating equal opportunity societies. It is known that certain transmitted characteristics are rewarded in the labour market which naturally renders $\beta > 0$. However, a judgement on socially optimal intergenerational transmission of incomes requires a profound understanding of the transmission process (Atkinson, 1981).

The literature on intergenerational mobility can be divided into three main strands. The early literature estimated various intergenerational correlations of economic status. Later research paid attention to the correct measurement of economic status and improved IGE estimates. Recent work has been dedicated to the identification of the underlying income transmission mechanism. The work has concentrated on males as the estimation of females' economic status is impeded by their more complex labour supply structure (Solon, 1999).

The early literature, surveyed and formalised by Becker and Tomes (1986), obtains estimates of intergenerational persistence in incomes, wealth, consumption, occupations and education. From here, the consensus emerges that measures of earnings are suitable proxies of lifetime welfare as they are highly correlated with the other relevant economic measures. The importance of investments into human capital for economic mobility and economic inequality has been emphasised. The main finding of

[1] There is a theoretical possibility of $\beta = -1$, implying the complete reversal of economic status from one generation to another. Also, $|\beta| > 1$ is conceivable and implies divergence from the group mean (Atkinson, 1981). Neither value of β has been observed in empirical analyses.

this wave of research, mainly conducted in the US, is a high degree of societal mobility, in which "disadvantages of ancestors are wiped out in three generations" (Becker and Tomes, 1986).

2.2 Measurement challenges

The second strand of literature concentrated on econometric problems in the estimation of economic status and IGEs arising through data limitations on individuals' lifetime earnings. Solon (1992) and Zimmerman (1992) demonstrated the existence of pronounced measurement errors when lifetime earnings were approximated by single income observations. Under the assumption of classical measurement errors[2], estimates of the IGE β are attenuated by the signal-to-noise ratio in measured variables. Based on US data, Solon and Zimmerman show that IGE estimates are considerably higher when income observations are averaged over multiple periods, which provides strong evidence for measurement errors in single year income observations.

Further research has identified lifecycle patterns in individuals' earnings streams as another source of inconsistencies in IGE estimation, which deviates from classical errors-in-variables. Pioneering work by Jenkins (1987) isolated errors arising through the age at which income is measured and through the age difference between parents and children and their varying stages in their lifecycle. More recently, Haider and Solon (2006) suggest observed one-period earnings to be a composition of an age-dependent fraction λ_a of lifetime earnings y_{ij} and age-dependent random noise v_{ija},

$$y_{ija} = \lambda_a y_{ij} + v_{ija}. \tag{2}$$

They show that the direction of bias in IGE estimations cannot be unambiguously determined as it varies by age at which incomes are observed. A detailed technical exposition is provided in the outline of the econometric strategy in section 3.3.2. Lindquist and Böhlmark (2005) test the model with Swedish data and find variations in lifecycle patterns by gender and cohorts. Pfeiffer and Eisenhauer (2008) use German data to show that the bias also varies by ability types. These findings are of importance for empirical research on group differences in economic mobility. It was found that the lifecycle bias is most pronounced for income observations of sons in their 20s, while it is minimised when incomes are observed in the 30s and early 40s.

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[2] Measured income $y_{0j} = y^*_{0j} + v_{0j}$, where y^*_{0j} is the true value and $v_{0j} \sim N(0, \sigma_v^2)$. $Cov(v_{0j}, y^*_{0j}) = 0$, $Cov(v_{0j}, \varepsilon_{1j}) = 0$

The main intuitive conclusion derived from this strand of literature is a higher persistence in economic status than presumed in Becker and Tomes (1986). It remains unclear which mechanism underlies the intergenerational income transmission process.

2.3 The transmission mechanism

The third strand of literature has focused on this transmission mechanism. Generally, there are two potential sources of determinants to distinguish: institutional factors of an economy and family background related factors (Black and Devereux, 2011).

As data have become available, international IGEs have been re-estimated and compared across countries and time. Solon (2002) and Jäntti *et al.* (2006) point out that Nordic European countries exhibit a higher economic mobility than the UK and the US. As these countries differ substantially in terms of institutions and public policy, it has been suggested that these factors can account for differences in the intergenerational persistence in economic status (Black and Devereux, 2011). Solon (2004) associates these variations with regional differences in returns to education, differences in the efficacy and the amount of public investments in schooling and the transmission of rewarded traits. Research by Mayer and Lopoo (2008) and Ichino *et al.* (2011), using cross-regional comparisons, presents a negative correlation between public investment in education and income elasticity estimates, suggesting a higher economic mobility where public investments in education are higher. Machin (2007) confirms the generally equalising effect of education on the income distribution. Overall, education seems to be an important moderator of income mobility.

Many researchers found a large amount of educational transmission from parents to children themselves, which has been attributed to the following mechanisms: Parents with higher education on average have higher incomes and could invest more in offspring education. Further, they could increase the efficacy of education through better support as well as an efficient allocation of time and household expenditures in child-promoting activities. Finally, personal traits and abilities, which might foster higher educational attainments, could be transmitted between generations (Black and Devereux, 2011).

Bowles and Gintis (2002) studied differences between identical twins and fraternal twins and identified substantial differences in income persistence implying an important role for inherited genetics.[3] A decomposition of IGEs into direct and indirect effects suggests that ability and educational attainments can explain 60 per cent of the intergenerational persistence.

In recent years, research moved on to investigating personal characteristics as a source of persistence preceding moderators such as education. It aims at revealing the degree of intergenerational resemblance in personal traits and attitudes and their impact on economic outcomes. However, this research is fraught with obstacles. First, there are severe data limitations on personal characteristics as they are rarely measured and mostly self-reported. Moreover, these characteristics are correlated with other potentially important determinants of income mobility (Black and Devereux, 2011).

Research on twin data, for example, provides strong evidence of a causal relationship between health states across generations (Black *et al.*, 2007). It was also found that IQs have high intergenerational associations (Black *et al.*, 2009). This finding complements work by Blanden *et al.* (2007), who address the role of cognitive and non-cognitive ability, educational attainment and labour market attachment in the transmission process behind intergenerational earnings persistence. They find that cognitive and non-cognitive characteristics are significantly correlated with parental incomes and are rewarded in the labour market, which provides a source of intergenerational persistence. Their impact on income persistence mainly seems to be intermediated by education. Osborne Groves (2005) addresses the role of personality directly. She uses a decomposition approach and finds that personal traits can account for 11 per cent of the father-son earnings correlation. However, the contributions on the role of ability and personality are at most suggestive of the transmission mechanism, as their selection-on-observables strategy is unable to identify causal effects and is sensitive to omitted variables.

Other work examined the transmission of attitudes and behaviour, such as working hours preferences, donation-giving or risk attitudes (Black and Devereux, 2011). Dohmen *et al.* (2006) find that risk and trust attitudes feature a substantial positive correlation between parents and children. In 2009, they also find that risk averse

[3] A large body of literature, which tries to explain the transmission mechanism, uses creative research approaches with data on twins, adoptees, biological and stepparents to identify family background and neighbourhood influences. The general consensus is that both matters, though family is more important than neighbourhood. The impact exhibits regional differences in magnitude. Björklund *et al.* (2007) use a rich data set which allows valuable insight. Solon (1999) and Black and Devereux (2011) provide comprehensive surveys of this strand of literature.

individuals tend to be more impatient and exhibit lower cognitive abilities. As risk attitudes impact many economic decisions, they could constitute an important determinant of intergenerational income persistence. For example, different occupations are associated with varying degrees of health and earnings risks. Bonin *et al.* (2007) confirm high correlations of individual risk attitudes and occupational choice. It was also found that occupational choices exhibit significant intergenerational correlations (Becker and Tomes, 1986).

Educational decisions, which suggestively are important mediators of income mobility, are associated with great uncertainty about own abilities, the right matching with the curriculum, passing final exams and the eventual value of acquired knowledge in the labour market (Becker, 1993, Hartog *et al.*, 2004). From theory, it follows that given a level of uncertainty, risk taking individuals invest more into human capital than their risk averse peers (Levhari and Weiss, 1974, Becker, 1993). The extensive literature on returns to education has not addressed potential heterogeneities in returns to education by risk attitudes (Hartog *et al.*, 2004), which could shed light on varying degrees of investment. Although the hypothetical link is important, the scarce empirical work has identified at most a small role for own risk attitudes (Belzil and Leonardi, 2007). Only one recent study assigns a role to parental risk attitudes on children's educational outcomes and identifies a higher probability of college attendance when parents tend to take more risk (Brown *et al.*, 2012).

IGEs have become a conventional summary measure of intergenerational mobility as they are informative on the pace at which certain groups converge to the group mean. However, they hide information which might be important for better understanding the transmission mechanism. For example, IGEs do not distinguish upward and downward mobility nor are they conclusive on the ability to move through the entire earnings distribution. Recent work suggests informative summary measures which are more suitable for group comparisons. Hertz (2005) puts within-group elasticities and between-group elasticities forward. Bhattacharya and Mazumder (2011) propose directional rank mobility for capturing the conditional probability of income rank changes between generations. However, these new measures have received little attention in empirical work so far.

3 Research hypotheses and econometric strategy

3.1 Research hypotheses

This study will build on Dohmen *et al.* (2006), who identified intergenerational correlations of risk attitudes. The research hypotheses of this study are:

H1: *A higher willingness to take risks, of fathers or sons, favours intergenerational mobility in education and incomes.*

The first hypothesis rests on three arguments made in the literature. First, individuals with a higher willingness to take risk were found to experience higher income growth and volatility which could favour intergenerational income differences (Shore, 2011). Second, education is a suggestively important moderator in the income transmission process; higher educational similarities are associated with higher income similarities (e.g. Jäntti *et al.*, 2006, Solon, 2004, Machin, 2007). As education decisions exhibit great uncertainty, theory suggests an important interference with individuals' risk attitudes (Becker, 1993).

H2: *Educational choices are more impacted by parental risk attitudes than own risk attitudes.*

Educational decisions are made at early stages in life and are associated with great uncertainty. Children may consider parental advice to expand their information set. This advice incorporates parental risk attitudes, which interact with parental ability and economic status (Dohmen *et al.*, 2009). This completes an important channel through which economic status could persist across generations. Figure 1 outlines the suggested transmission scheme.

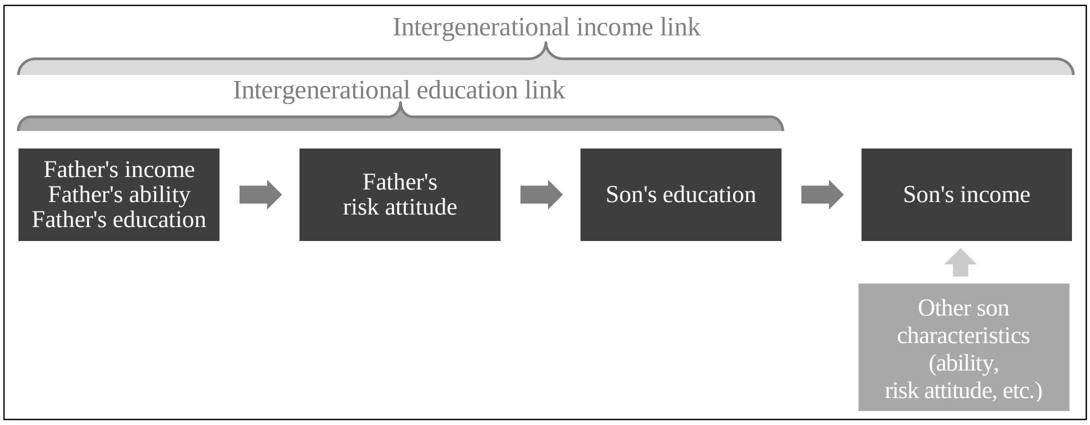


Figure 1 - Hypothesised transmission mechanism for intergenerational income mobility

3.2 Econometric strategy

The first part of the analysis addresses H1. I estimate intergenerational income elasticities separately by sons' risk attitudes and by their fathers' risk attitudes. This identifies differences in income mobility across generations, and is suggestive of the intensity of the income link depicted in figure 1. This is followed by estimations of educational mobility for these groups, as this could illuminate the source of differences in income mobility. If education was an important transmission channel, one would expect higher educational mobility for those groups that exhibit higher income mobility as well.

The second part of the analysis addresses H2 and examines the link between risk attitudes and education in more detail. Multiple regression analysis aims at isolating the direct effect of risk attitudes on investments in education. It is further checked whether heterogeneous returns to education can explain group differences in educational investments, as theory suggests higher investments where returns to investments are higher, ceteris paribus (Kocherlakota, 1996).

In order to circumvent further sources of biases and to simplify the econometric model, the analysis concentrates on fathers and sons. For ease of reference, the following wording convention will be obeyed: The phrasing *risk averse sons* refers to the group of sons reporting a relatively low willingness to take risk. The phrasing *risk taking sons* refers to the group of sons reporting a relatively high willingness to take risk. *Sons of risk averse fathers* refers to sons whose fathers reported a relatively low willingness to take risk. *Sons of risk taking fathers* refers to sons whose fathers reported a relatively high willingness to take risk. References to *family risk attitudes* mean sons' own and their fathers' risk attitudes.

3.3 Estimation of intergenerational mobility

3.3.1 Group differences in intergenerational mobility

The common regression approach for the estimation of intergenerational mobility in incomes relates sons' log incomes y_{Sj} and their fathers' log incomes[4] y_{Fj},

$$y_{Sj} = \alpha + \beta y_{Fj} + \varepsilon_{Sj}, \tag{3}$$

where ε_{Sj} is an error term capturing variation in sons' log incomes which cannot be explained by variations in fathers' log incomes. The coefficient β is referred to as the intergenerational elasticity of earnings (IGE, Solon, 1999). It measures the total statistical association between incomes of both generations. Children with parents earning one per cent above the mean income are expected to earn β per cent above the mean. For this reason, this estimation is referred to as regression to the mean. The coefficient β can be interpreted as the intergenerational *persistence* in incomes; a higher β value denotes a stronger intergenerational link of incomes. The rate at which sons' incomes convert to the mean income is $(1 - \beta)$. It is interpreted as a measure of *mobility*.

Including further covariates into the regression decomposes the summary measure β into its direct and indirect effects (Bowles and Gintis, 2002). One can write

$$y_{Sj} = \alpha + \beta y_{Fj} + Z^{'}\gamma + \varepsilon_{Sj} \tag{4}$$

with Z as a vector comprising variables of individual characteristics. If the inclusion of control variables changes the coefficient $\beta,$ this control variable captures variations in sons' incomes that have previously been captured by similar variations in fathers' incomes y_{Fj}. The identification of group differences in the intergenerational income mobility results from an inclusion of an interaction term in equation (4), indicating a certain group affiliation. This allows for group variations in the intercept term and the slope parameter. The final model becomes

$$y_{Sj} = \alpha_1 + \alpha_2 D_{Sj} + \beta_1 y_{Fj} + \beta_2 D_{Sj} * y_{Fj} + Z^{'}\gamma + \varepsilon_{Sj}. \tag{5}$$

If son S of family j is risk taking, D_{Sj} takes the value one, zero otherwise. For $D_{Sj} = 1$, the slope parameter denoting the IGE is $(\beta_1 + \beta_2)$; for $D_{Sj} = 0$, the IGE is β_1. If D indicates sons' risk group affiliation, the coefficient β_2 indicates differences in intergenerational incomes mobility between risk averse and risk taking sons. If D

[4] Empirical work conventionally logarithmises incomes to ensure an approximate normal distribution of log incomes and homoscedastic distribution of error terms.

indicates the risk group of sons' fathers, β_2 indicates differences in intergenerational incomes mobility between sons of risk averse and risk taking fathers.

The analysis of differences in educational mobility also builds on equation (5), where y_{Sj} and y_{Fj} then denote sons' and fathers' levels of education, respectively, with β_2 indicating group differences in educational mobility.

3.3.2 Approximation of lifetime earnings

The estimation of IGEs requires the approximation of individuals' lifetime incomes. As noted in section 2.2, this approximation is confronted by measurement errors. Haider and Solon (2006) have shown that this error varies with individuals' position in their lifetime earnings profile, which depends on age and ability. Typical earnings profiles and the resulting averages are sketched in figure 2. Individuals with higher cognitive ability and expectedly higher lifetime earnings exhibit a steeper income growth path in early years of their labour market experience. Consequently, early income observations are misrepresentative in reflecting the actual earnings capacity.

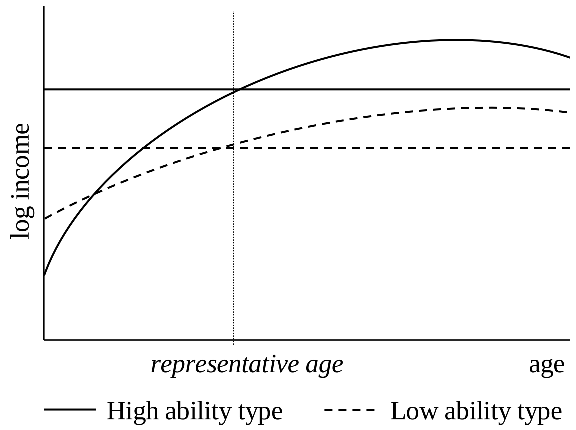


Figure 2 – Lifetime income profiles by ability types (source: Haider and Solon, 2006).

The measurement error biases IGE estimates through both the dependent variable and the independent variable. For simplicity of illustration, the demonstration builds on the model of equation (3). It is also assumed that y_{Fj} and y_{Sj} are measured as deviations from the population mean, which removes the intercept term α. The measurement error in the *dependent* variable can be formalised by

$$y_{Sja} = \mu_a y_{Sj} + v_{Sja}. \tag{6}$$

where y_{Sja} denotes the log income of the sons of family j at age a, which is equal to the lifetime earnings y_{Sj} multiplied by an age varying factor μ_a. The error term v_{Sja}

captures transitory fluctuations in observed income and is assumed to be independent of y_{Sj}. The actual model for estimation becomes

$$y_{Sja} = \mu_a \beta y_{Fj} + \mu_a \varepsilon_{Sj} + v_{Sja}.$$

The probability limit of $\hat{\beta}$ is

$$plim\hat{\beta} = \frac{Cov(y_{Sja}, y_{Fj})}{Var(y_{Fj})} = \frac{Cov(\mu_a \beta y_{Fj} + \mu_a \varepsilon_{Sj} + v_{Sja}, y_{Fj})}{Var(y_{Fj})}$$

$$plim\hat{\beta} = \beta\mu_a \tag{7}$$

For any $\mu_a \neq 1$, β is inconsistent. This is most pronounced when sons are young as μ_a is small.

The measurement error can also occur in the independent variable y_{Fj}, fathers' log incomes,

$$y_{Fja} = \lambda_a y_{Fj} + v_{Fja}.$$

Assuming that the dependent variable is correctly measured, the model of equation (3) becomes

$$y_{Sj} = \beta(\frac{1}{\lambda_a} y_{Fja} - \frac{1}{\lambda_a} v_{Sja}) + \varepsilon_{Sj}.$$

The probability limit of $\hat{\beta}$ is

$$plim\hat{\beta} = \frac{Cov(y_{Sj}, y_{Fja})}{Var(y_{Fja})} = \frac{Cov\left(\beta(\frac{1}{\lambda_a} y_{Fja} - \frac{1}{\lambda_a} v_{Sja}) + \varepsilon_{Sj}, y_{Fja}\right)}{Var(y_{Fja})}$$

$$= \frac{Cov\left(\beta(\frac{1}{\lambda_a} y_{Fja} - \frac{1}{\lambda_a} v_{Sja}) + \varepsilon_{Sj}, \lambda_a y_{Fj} + v_{Fja}\right)}{Var(y_{Fja})}$$

$$= \frac{\beta\, Cov(y_{Fja}, y_{Fj})}{Var(y_{Fja})} + \frac{\beta}{\lambda_a} \frac{Var(v_{Fja})}{Var(y_{Fja})} - \frac{\beta}{\lambda_a} \frac{Var(v_{Fja})}{Var(y_{Fja})}$$

$$= \frac{\beta\, Cov(\lambda_a y_{Fj} + v_{Fja}, y_{Fj})}{Var(\lambda_a y_{Fj} + v_{Fja})} = \beta \frac{\lambda_a\, Var(y_{Fj})}{\lambda_a^2 Var(y_{Fj}) + Var(v_{Fja})}$$

$$plim\hat{\beta} = \beta\theta_a \qquad \text{where } \theta_a = \frac{\lambda_a\, Var(y_{Fj})}{\lambda_a^2 Var(y_{Fj}) + Var(v_{Fja})} \tag{8}$$

The parameter θ_a can be referred to as the inconsistency factor differing with age of considered income observations.

If measurement errors arise in the dependent and independent variable, the overall probability limit is

$$plim\hat{\beta} = \beta\mu_a\theta_a. \tag{9}$$

It can be shown that with $\lambda_a < 1$ and a small ratio of $\frac{Var(v_{Fja})}{Var(y_{Fj})}$, θ_a can exceed one and introduce an amplification bias to the estimation of β (Solon, 2006). For $\lambda_a = \mu_a = 1,$ so earnings were observed at a representative age, the bias reduces to an attenuation bias due to classical errors-in-variables described in Solon (1992) and Zimmerman (1992). They demonstrate that this bias reduces as the number of averaged income observation for father's income increases[5] because the impact of transitory fluctuations declines. The inconsistency factor θ becomes

$$\theta = \frac{Var(y_{Fj})}{Var(y_{Fj}) + \frac{Var(v_{Fj})}{T}}$$

In coping with measurement errors, this study excludes income observations before age 30 and after age 60, which reduces lifecycle biases. Moreover, income observations of fathers and sons are averaged over at least three periods to reduce transitory fluctuations. Further details on the definition of individuals' lifetime incomes that are used in this empirical analysis are provided in section 4.2.

The analysis of educational mobility has lower data restrictions as there is no source of lifecycle bias in reported schooling. Education is mainly completed when individuals enter the labour market (Black and Devereux, 2011).

3.4 Explorative multiple regression analysis

The link between family risk attitudes and educational attainments is explored with multiple regression analysis. The following description follows Wooldridge (2009).

Simple linear regression analysis captures the simultaneous statistical association of any direct and indirect correlation of risk attitudes and education. One can write

$$E_{Sj} = \alpha + \beta D_{Sj} + \varepsilon_{Sj}$$

with E_{Sj} denoting educational attainments of son S of family j. D_{Sj} denotes again fathers' or sons' risk group affiliation. Idiosyncratic noise is captured by ε_{Sj}. The model can be expanded by the inclusion of control variables in vector Z_{Sj} accounting directly for their correlation with the dependent variable:

$$E_{Sj} = \alpha + \beta D_{Sj} + Z_{Sj}^{'}\gamma + \varepsilon_{Sj}.$$

The interpretation of β becomes a ceteris paribus interpretation on the association between education levels and family risk attitudes after having controlled for other

[5] Classical measurement errors in the dependent variable do not result in estimation inconsistencies.

potential determinants of education. A stepwise inclusion of further control variables can approach a causal interpretation of $\hat{\beta}$(Wooldridge, 2009). The first model captures the direct statistical association between family risk attitudes and educational attainments. The second model controls for family background, including a quadratic term for fathers' years of education and income, and dummy variables indicating fathers' highest educational degree. The third model additionally controls for individual characteristics, including son's health status and body height, as well as a time fixed effect for generational changes in education levels.

Throughout, any interpretation of $\hat{\beta}$ must be aware of biases arising through omitted variables. Given is the estimator $\hat{\beta}$,

$$\hat{\beta} = \frac{Cov(E_{Sj}, \tilde{D}_{Sj})}{Var(\tilde{D}_{Sj})},$$

$\tilde{D}_{Sj}$ denotes residuals of a regression of D_{Sj} on Z_{Sj}, hence the remaining variation in the risk variable which is not explained by variations in control variables. The inconsistency in $\hat{\beta}$ arising through omitted variables can be illustrated by the probability limit of $\hat{\beta}$:

$$plim\,\hat{\beta} = \frac{Cov\left(\beta\tilde{D}_{Sj} + \varepsilon_{Sj}, \tilde{D}_{Sj}\right)}{Var\left(\tilde{D}_{Sj}\right)}$$

$$plim\,\hat{\beta} = \beta + \frac{Cov(\varepsilon_{Sj}, \tilde{D}_{Sj})}{Var(\tilde{D}_{Sj})}.$$

Therefore, this empirical strategy is suitable for an exploration of the statistical relationship between family risk attitudes educational attainments, but it is not conclusive on causal effects.

3.5 Estimation of returns to education

The examination of heterogeneous private returns to education faces strong data limitations and requires assumptions in order to recover missing counterfactuals. Two approaches with varying assumptions are implemented to provide higher robustness of results. The analyses build on Mincer's Human Capital Earnings Function (HCEF, 1974) which models individual log incomes as a linear composition of years of schooling, E, and a quadratic term of potential working experience, X:

$$y_i = \alpha + \beta E_i + \gamma X_i + \delta X_i^2 + \varepsilon_i$$

with ε_i denoting a random error term. This specification produces inconsistent estimates of β when estimated with Ordinary Least Squares (OLS) regression, as the error term ε is likely to comprise factors of family background and cognitive ability, which are believed to be correlated with the endogenous educational choice and labour market outcomes (Card,1999, Altonji and Dunn,1995).

The first analysis augments Mincer's HCEF to account for the outlined problem and also to allow for identification of heterogeneous returns to education by observable characteristics (Altonji and Dunn, 1995). The general model can be expressed by

$$y_{ij} = Z_{ij}^{'}\gamma + \beta_{ij}E_{ij} + \varepsilon_{ij} + \varepsilon_j \tag{10}$$

where y_{ij} is the log income of individual i in family j, Z_{ij} is a vector containing individual and background specific characteristics, E_{ij} are individual i's years of education, ε_{ij} and ε_j are individual and family specific error terms which are assumed to be uncorrelated with E_{ij} after having controlled for Z_{ij}. The coefficient β_{ij} captures the marginal returns to education, which can vary by individual observable characteristics,

$$\beta_{ij} = \beta_1 + \beta_2 D_{ij} + \eta_{ij} + \eta_j \tag{11}$$

where β_1 are average marginal returns to education, η_{ij} and η_j are household and individual specific components in these returns that are assumed to be uncorrelated with D_{ij}, a vector of person-specific characteristics according to which returns vary. Substituting (11) into (10) yields

$$y_{ij} = Z_{ij}^{'}\gamma + (\beta_1 + \beta_2 D_{ij})E_{ij} + \varepsilon_{ij} + \varepsilon_j + (\eta_{ij} + \eta_j)E_{ij}. \tag{12}$$

In an econometric model, this can be written as

$$y_{ij} = Z_{ij}^{'}\gamma + \beta_1 E_{ij} + \beta_2 D_{ij} * E_{ij} + u_{ij} \tag{13}$$

where $u_{ij} = \varepsilon_{ij} + \varepsilon_j + (\eta_{ij} + \eta_j)E_{ij}$. An unbiased OLS estimation of β_2, the coefficient of main interest, requires the error term u_{ij} to be independent of $D_{ij} * E_{ij}$. This critically depends on the availability of control variables and the independence of person specific variations in returns to education $(\eta_{ij} + \eta_j)$ from E_{ij}, the level of education.

In the estimation of this study, D_{ij} indicates family risk attitudes. The vector Z_{ij} comprises controls for individuals' labour market characteristics, namely quadratic terms for firm tenure, age and potential years of working experience, as well as linear terms of health status and body height. The vector also includes fathers' education to control for family background, as well as fathers' and sons' risk attitudes.

Though this strategy would allow controlling for ability and family background, the available data set does not provide sufficient information on individuals' cognitive abilities. If years of schooling and the interaction term are positively correlated with ability, estimates are likely to be upward biased. Ability is commonly believed to be positively correlated with schooling (Card, 1999). The correlation between risk attitudes and cognitive ability was also found to be positive (Dohmen *et al.*, 2009). Therefore, one would expect $\hat{\beta}_2$to be upward biased (Altonji and Dunn, 1995).

The second model addresses the potential source of bias with a family fixed effect model. It assumes that education is merely correlated with a fixed family ability component. An adopted version[6] of Altonji and Dunn (1995) expresses the homogenous returns to education model of equation (12) for each household member:

$$y_{Sj} = Z_{Sj}^{'}\gamma_S + \beta_{S1}E_{Sj} + \varepsilon_{Sj} + \varepsilon_j \tag{14}$$

$$y_{Fj} = Z_{Fj}^{'}\gamma_F + \beta_{F1}E_{Fj} + \varepsilon_{Fj} + \varepsilon_j \tag{15}$$

The subscripts S and F denote son and father of family j.

The main assumption required for identification is that unobserved household characteristics, which impact education, persist through generations. For example, if innate ability is correlated with education, it is assumed to be the same for fathers and sons. Second, labour market returns to individual characteristics are time invariant, hence $\gamma_S = \gamma_S = \gamma,\ \beta_{S1} = \beta_{F1} = \beta_1$. Taking the difference of equations (14) and (15) yields

$$\Delta y_j = y_{Sj} - y_{Fj} = \left(Z_{Sj}^{'} - Z_{Fj}^{'}\right)\gamma + \beta_1\left(E_{Sj} - E_{Fj}\right) + (\varepsilon_{Sj} - \varepsilon_{Fj})$$

$$= \Delta Z_j'\gamma + \beta_1\Delta E_j + \Delta\varepsilon_j.$$

If the difference in idiosyncratic error terms $\Delta\varepsilon_j$ is independent of differences in schooling, returns to education, β_1, can be consistently estimated with OLS. The inclusion of an interaction term, indicating the individual's risk attitude or that of his father, can identify risk group differences in returns to education. The second empirical model finding application in this study hence is

$$\Delta y_j = \Delta Z_j^{'}\gamma + \beta_1\Delta E_j + \beta_2 D_j * \Delta E_j + \varphi D_j + \Delta\varepsilon_j. \tag{16}$$

[6] The data available comprise information on fathers and sons, which restrains from directly accounting for heterogeneity in different groups of risk attitudes. A family fixed effect model identifying heterogeneous returns to education is outlined in Altonji and Dunn (1995).

The vector of control variables ΔZ_j comprises differences in age, firm tenure, experience, health, height and risk attitudes between son and father, which all might be associated with labour market returns.

The model is flexible to be applied as a single-treatment model as well, for example to identify differences in returns to a university degree (Altonji and Dunn, 1995). The variable E then takes the value one if an individual holds a university degree, zero otherwise. This flexibility will be used for robustness checks.

4 Data

The empirical analysis of the relationship between family risk attitudes and economic mobility imposes rigorous data requirements. The German Socio-Economic Panel Survey seems most suitable for this analysis, as it provides reliable information on individuals' incomes and socio-economic backgrounds and allows for matching of parents and their children. Moreover, it contains information on risk attitudes for both generations. This section describes the data set and sample selection procedure, as well as the definition of core variables for this study. It furthermore provides descriptive statistics and basic statistical intergenerational associations between family risk attitudes, education levels and incomes.

4.1 Description of the German Socio-Economic Panel Survey

The German Socio-Economic Panel Survey (SOEP) is a representative panel data set on the German resident population. The survey was launched in 1984 and has been repeated on an annual basis. By 2008, the SOEP contained nearly 11,000 households and almost 20,000 responding individuals.

The survey provides information for each household member aged 17 years and older and is conducted in separate personal interviews to guarantee independent answers of household members. The SOEP collects personal and household information, and also conducts irregular surveys on specific topics. An additional survey of particular interest for the present study asked for individual risk attitudes in the wave of 2004.

A useful feature of the survey is the continued tracking of different family members when they move to form a separate household. Children leaving the parental household are asked to further participate in the survey. This allows matching of family members in different generations. A more detailed documentation of the panel survey is provided by Wagner *et al.* (2007).

4.2 Sample selection and variable definitions

This empirical study uses data from 1984 to 2009 and focuses on full-time employed males from West Germany. The exclusion of females is the result of modelling difficulties arising from complex labour supply patterns (Killingsworth and Heckman, 1987). Observations from East Germany are excluded as they exhibit a structural break in 1989 in their biography which on average led to a strong increase in professional and geographic mobility as well as unrepresentative, strong wage growth (Hunt, 2002). Furthermore, an extra sample over-representing high income households has been discarded.

I match fathers and sons and keep multiple sons with the same father in the sample in favour of a larger sample size. Depending on the actual subsample, the sample size increases by 69 to 90 observations but potentially introduces some sample homogeneity (Black and Devereux, 2011). Moreover, the voluntary participation in the panel survey could lead to an overrepresentation of families with stronger cohesion when children with closer links to their parents remain in the sample. As the difference in income mobility is in the focus of the analysis, sample homogeneity and an overrepresentation of families with closer links is unproblematic as long as their extent does not vary by groups of different risk attitudes.

The analysis requires several variables to be generated from available data. The approximation of lifetime incomes is based on the panel's annual information on last month's gross labour income in Euro. For most people, labour income is the main source of income and highly correlated with consumption and the welfare of an individual (Becker and Tomes, 1986). Gross labour incomes reflect the valuation of individual capabilities in the labour market, independent of time- and group-specific social security and tax deductions. I discard income observations for males in unemployment, part-time employment, vocational training or education, imputed incomes[7] and observations smaller than 200 Euro, as they have been classified as unreliable (Couch and Dunn, 1997, Pfeiffer and Eisenhauer, 2008, Dustmann *et al.*, 2009). The reported monthly gross labour income is deflated to a common base year using the Consumer Price Index for Germany in order to make incomes comparable across years.[8]

Following the outlined strategy to minimise sources of errors in lifetime incomes, the final variable is generated as the mean of three or more log real income observations between age 30 and 60. Father-son pairs with fewer observations for each generation are removed from the sample.

Another variable of core interest is the self-reported risk attitude. The original phrasing of the relevant survey question was the following: "How do you see your-

[7] The SOEP estimates gross labour incomes based on Mincer wage regressions where reported incomes are occasionally missing.
[8] Source: OECD stats, consumer prices (main economic indicators), 1984-2009, base year=2005.

self: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?” Individuals had to rank themselves on an 11-point-scale from zero, indicating absolute risk aversion, to ten, indicating full risk taking. Dohmen *et al.* (2005) have shown that these self-reported risk attitudes are valuable predictors of individual behaviour in experiments testing their actual risk attitudes. This confirms the validity of the self-reported risk attitudes as proxy for their actual risk attitudes. In order to account for time- and age-varying shifts in individuals’ risk perceptions and to allow for intergenerational comparisons in relative positions in the risk distribution, a standardisation has been undertaken using the full sample and the distinction of three generations. The definition of a generation accounts for the following factors. First, subsample sizes should be sufficiently large. Also, it should be intuitive and account for historical breaks which might impact socio-economic characteristics. Finally, no father-son pair should appear in the same generation to make comparisons of the relative position in the generational risk distribution meaningful. The first generation covers birth cohorts born before and during World War II (808 observations), the second generation contains post-war cohorts up to 1960 (1771 observations) and the third generation covers all males born after 1960 (2091 observations). As can be seen from table 1, mean risk attitudes differ considerably across generations which could arise through age differences at the time risk attitudes were measured (Dohmen *et al.*, 2005).

TABLE 1 — RISK ATTITUDES AND INCOMES BY GENERATION

	Generation 1: Born before 1946	Generation 2: Born between 1946-1960	Generation 3: Born after 1960
N	808	1771	2091
Mean original risk	3.939	4.845	5.188
attitude[A]	(2.505)	(2.201)	(2.144)
Mean real income	2911.17	3147.17	2950.08
	(1367.94)	(1566.30)	(1345.33)
Min./max. real income	550.48/18802.00	241.64/18514.33	312.78/33139.24
Mean age when risk	65.404	50.401	36.641
attitude was measured	(5.070)	(4.302)	(4.263)

Notes: The table reports risk attitudes and mean real income by three distinct generations. Real income is measured in 2005 EUR. Standard deviations are in parentheses. [A] The risk attitude was measured on a scale from zero (fully risk averse) to ten (fully risk taking).

Standardised risk attitudes have a generational mean of zero and a standard deviation of one. An individual is relatively risk taking if his standardised reported risk attitude is bigger than zero. This indicates that he is in the upper half of the risk distribution in his generation. Where a dummy variable indicates family risk attitudes, it takes the value one if the son or his father has a standardised risk attitude bigger than zero.

As the remaining data set is of cross-sectional structure, time varying characteristics such as years of firm tenure, working experience and health state[9] have been averaged over the years for which income information has been provided. The variable measuring years of education uses the latest reported value, which also accounts for an increase of the level of education during work life. A proxy variable for cognitive ability would have been useful in the analysis, but has not been available for the majority of observations in the sample.

The resulting sample contains 365 father-son pairs, for which descriptive statistics are provided in table 2. The analysis of intergenerational education mobility does not require income information and has consequently less restrictive data requirements. The sample size of this section increases to 1214. Descriptive statistics are presented in table 3.

[9] The state of health is a discrete variable measuring the self-reported health state on a scale ranging from one (very good) to five (bad).

TABLE 2 — DESCRIPTIVE STATISTICS FOR NARROW SAMPLE

	Pooled	Grouped by sons risk attitudes		Grouped by Fathers' risk attitudes	
		Risk averse	Risk taking	Risk averse	Risk taking
N	365	197	168	275	90
Sons					
Monthly mean log real income	7.930 (0.394)	7.879 (0.387)	7.990 (0.394)	7.931 (0.393)	7.927 (0.398)
Min./max. monthly log real income	6.234/9.405	6.234/9.405	6.358/ 8.835	6.234/9.405	6.358/8.608
Mean years of education	12.686 (2.940)	12.381 (2.927)	13.045 (2.925)	12.478 (2.912)	13.322 (2.953)
Min./max. years of education	7/18	7/18	7/18	7/18	9/18
Mean age in years	34.596 (2.521)	34.740 (2.590)	34.428 (2.435)	34.723 (2.608)	34.208 (2.202)
Mean height in cm	179.720 (6.789)	179.704 (7.297)	179.739 (6.161)	179.151 (6.696)	181.457 (6.813)
Mean health state[B]	2.189 (0.573)	2.156 (0.528)	2.228 (0.621)	2.213 (0.600)	2.115 (0.476)
Mean firm tenure in years	7.912 (5.369)	7.805 (5.343)	8.038 (5.412)	7.994 (5.522)	7.664 (4.893)
Mean experience in years	10.844 (4.588)	11.119 (4.683)	10.522 (4.467)	11.053 (4.623)	10.207 (4.446)
Mean original risk attitude[A]	5.286 (2.096)	3.770 (1.503)	7.054 (1.034)	5.091 (2.124)	5.878 (1.895)
Mean number of wage observations	9.030 (4.467)	9.218 (4.687)	8.810 (4.197)	9.138 (4.606)	8.700 (4.018)
Fathers					
Monthly mean log real income	7.936 (0.369)	7.909 (0.345)	7.967 (0.394)	7.883 (0.333)	8.098 (0.424)
Min./max. monthly log real income	6.885/9.804	6.885/8.894	7.231/9.804	6.885/9.124	7.508/9.804
Mean original risk attitude[A]	3.822 (2.519)	3.513 (2.424)	4.185 (2.587)	2.764 (1.873)	7.056 (1.053)
Mean years of education	11.195 (2.548)	11.137 (2.632)	11.262 (2.451)	10.967 (2.400)	11.889 (2.858)
Mean age in years	51.285 (4.001)	51.515 (3.875)	51.015 (4.140)	51.440 (4.015)	50.811 (3.944)
Mean number of wage observations	13.192 (5.777)	13.046 (5.735)	13.363 (5.839)	12.807 (5.603)	14.367 (6.165)

Notes: Log real incomes are measured in 2005 EUR. Standard deviations are in parentheses. [A] The risk attitude was measured on a scale ranging from zero (fully risk averse) to ten (fully risk taking). [B] The health state was measured on a scale ranging from one (very good) to five (bad).

TABLE 3 — DESCRIPTIVE STATISTICS FOR WIDE SAMPLE

	Pooled	Grouped by sons' risk attitudes		Grouped by fathers' risk attitudes	
		Risk averse	Risk taking	Risk averse	Risk taking
N	1214	593	621	826	388
Sons					
Mean years of education	12.201 (2.617)	11.995 (2.624)	12.397 (2.597)	12.033 (2.595)	12.557 (2.634)
Min./max. years of education	7/18	7/18	7/18	7/18	7/18
Mean university degree	0.171 (0.376)	0.159 (0.366)	0.182 (0.386)	0.165 (0.371)	0.183 (0.387)
Mean original risk attitude[A]	5.482 (2.241)	3.637 (1.537)	7.243 (1.097)	5.197 (2.285)	6.088 (2.016)
Fathers					
Mean years of education	11.514 (2.557)	11.267 (2.484)	11.749 (2.604)	11.101 (2.307)	12.392 (2.830)
Min./max. years of education	7/18	7/18	7/18	7/18	7/18
Mean university degree	0.175 (0.380)	0.148 (0.356)	0.120 (0.400)	0.131 (0.337)	0.268 (0.444)
Mean original risk attitude[A]	4.320 (2.477)	3.821 (2.408)	4.797 (2.449)	3.019 (1.795)	7.090 (1.027)

Notes: Standard deviations are in parentheses. [A] The risk attitude was measured on a scale from zero (fully risk averse) to ten (fully risk taking).

4.3 Intergenerational statistical associations

Individual characteristics matter for the intergenerational income transmission process when they show correlations with fathers' income and when they are rewarded in the labour market (Blanden *et al.*, 2007). Panel (a) of table 4 reports regression results of family risk attitudes on fathers' incomes and on fathers' levels of education. Panel (b) reports regression results of sons' incomes and sons' levels of education on family risk attitudes. There certainly are strong statistical association among them. Figure 3 depicts the direct statistical association between family risk attitudes and sons' incomes and education. This also identifies a noticeable statistical link and gives reason to believe that risk attitudes are associated with intergenerational mobility in incomes and education.

TABLE 4 — RELATIONSHIP BETWEEN FAMILY RISK ATTITUDES, EDUCATION AND INCOMES

(a)

	Dependent variable:			
	Son's risk attitude[A]		Father's risk attitude[A]	
Independent variable:	(1)	(2)	(3)	(4)
Father's log real income	0.106		0.294***	
	(0.071)		(0.059)	
Father's years of education		0.018***		0.043***
		(0.006)		(0.005)
Constant	-0.377	0.299***	-2.084***	-0.175***
	(0.562)	(0.066)	(0.472)	(0.060)
R-squared	0.006	0.009	0.063	0.055
N	365	1214	365	1214

(b)

	Dependent variable:					
	Son's log real income			Son's years of education		
Independent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Son's risk attitude	0.111***		0.114***	0.402***		0.327**
	(0.041)		(0.041)	(0.150)		(0.152)
Father's risk attitude		-0.003	-0.021		0.523***	0.462***
		(0.048)	(0.048)		(0.160)	(0.163)
Constant	7.879***	7.931***	7.883***	11.995***	12.033***	11.886***
	(0.028)	(0.024)	(0.029)	(0.107)	(0.091)	(0.114)
R-squared	0.020	0.000	0.020	0.006	0.009	0.012
N	365	365	365	1214	1214	1214

Notes: The tables report coefficients from OLS regressions. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. [A] Dummy variable; it takes on the value one if sons or their fathers have risk attitudes in the top 50 per cent of the generational risk distribution, zero otherwise.

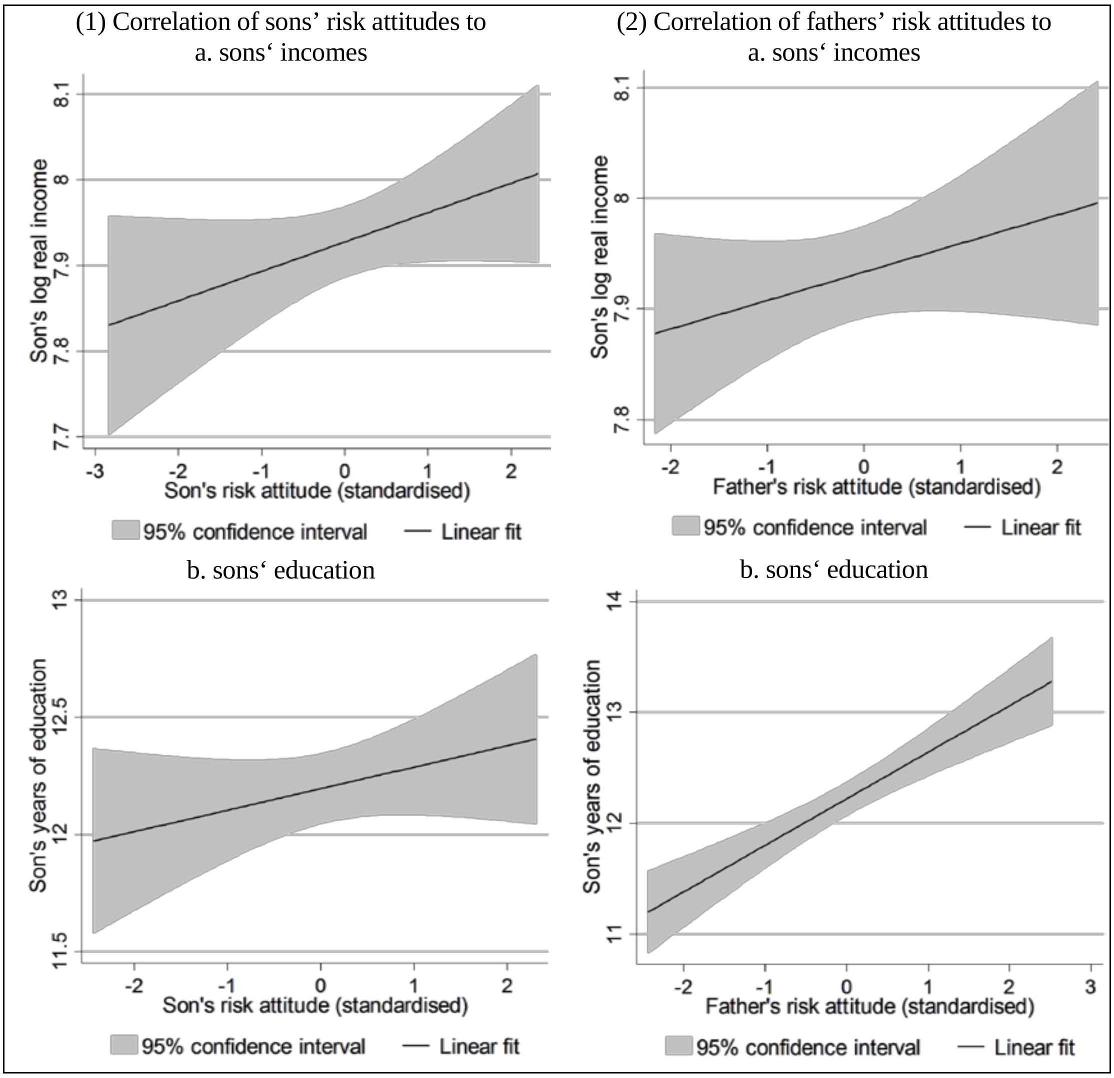


Figure 3 –Linear statistical associtation between family risk attitudes and sons' incomes and education

5 Results

The results are presented in two sections. Section 5.1 focuses on hypothesis 1 and identifies risk group differences in income mobility and educational mobility. Section 5.2 focuses on hypothesis 2 and analyses the link between educational attainments and family risk attitudes.

5.1 Intergenerational mobility of incomes and education

Section 5.1 reports intergenerational income elasticities and measures of educational persistence separately for sons' own and their fathers' risk attitudes in order to identify group differences in income mobility and educational mobility.

5.1.1 Intergenerational income mobility by risk attitudes

Table 5 presents the OLS estimation results for intergenerational income elasticities. The first column serves as reference point of the estimation results and allows a comparison to recent benchmark IGE estimates for Germany. Pfeiffer and Eisenhauer (2008) use SOEP information up to 2006 and estimate IGE based on 5-year averages of labour incomes observed at ages between 30 and 50. They find a point estimate of 0.282, which is near the estimate of 0.309 in this sample. Their standard error of 0.087 is higher as their sample incorporates only 180 father-son pairs. The higher point estimate in this study could arise from a positive lifecycle bias compared to Pfeiffer and Eisenhauer, which can be inferred from equation (9), $plim\hat{\beta} = \beta\mu_a\theta_a$. Sons in my sample are younger and on average 35.07 years old.[10] Following findings on lifecycle income paths by Haider and Solon (2006), which are illustrated in figure 2, $\mu_a$is presumably slightly smaller. More importantly, θ_a is likely to be larger in this sample as fathers are observed on average at age 51.5, while they were aged 44.4 in Pfeiffer and Eisenhauer. Assuming a constant ratio of $\frac{Var(v_{Fja})}{Var(y_{Fj})}$,

$\theta_a = \frac{\lambda_a\, Var(y_{Fj})}{\lambda_a^2 Var(y_{Fj}) + Var(v_{Fja})}$ increases as λ_a gets smaller in this sample due to later observations of fathers' incomes.

The IGE estimate for the full sample, reported in column 2 of table 5 is 0.291 and ranges below the value for 2006. This could arise through changes in the magnitude of a lifecycle bias as sons' average ages decreases by 0.47 to 34.60 with the inclusion

[10] In Pfeiffer and Eisenhauer (2008): Sons' mean age is 35.73 years; fathers' mean age is 44.40.

of all waves. This could decrease μ_a and attenuate the estimate according to equation (9). Alternatively, the average income mobility could have increased in recent years. The estimate implies that sons with fathers earning 10 per cent above the mean income are on average associated with incomes that are 2.9 per cent above the mean.

Column 3 distinguishes IGEs according to sons' risk attitudes. It appears that risk taking sons have slightly higher income mobility than risk averse peers, given the same parental risk attitude. The IGEs are 0.297 and 0.314 respectively. The precision of IGE estimates is too low to confirm the difference of 1.7 per cent with statistical significance. High standard errors arise through small sample sizes and the outlined sources of errors in the approximation of lifetime earnings. Column 4 controls for sons' education which leads to the opposite picture. Now, risk taking sons appear to have lower income mobility, implying that they are more dependent from their parents than risk averse sons, given the same parental risk attitude and the same level of education. In columns 5 and 6, where controls for family background and important labour market characteristics are introduced, this tendency remains unchanged. In the final specification, the difference of 0.9 per cent is negligible given the precision of estimates. In sum, there is no sign of higher income mobility for risk taking sons.

In columns 7 to 10, the IGE estimations for sons of risk averse and risk taking fathers are reported. Column 7 shows a 10.8 percentage points lower IGE for sons of risk taking fathers, implying higher income mobility than for sons of risk averse fathers, given the same risk attitude of sons. Again, the difference is statistically not significant. The income of sons with risk taking fathers is on average 2.4 percentage points above the mean when the father has an income which is 10 percentage points above the mean. For sons of risk averse fathers, the difference to the mean income is 3.4 percentage points. Regressions by risk groups show a lower R-squared for sons with risk taking fathers, implying less predictive power of paternal incomes on sons' incomes.[11] The former group therefore converges at a faster rate to the group mean and has higher income mobility. Column 8 reports the results when education is controlled for. The magnitude of elasticities strongly drops, but the group difference remains large. Further, controlling for family background reveals a strong positive correlation of fathers' incomes with fathers' education, inferred from the standard omitted variable bias and the significant negative association between sons' incomes

[11] This result follows from separate group estimations. Results are presented in table 14 and 15 in the appendix.

TABLE 5 — INTERGENERATIONAL PERSISTENCE IN INCOMES BY RISK ATTITUDES, DEPENDENT VARIABLE: SON'S MEAN LOG REAL INCOME

	1984-2006	1984-2009	By sons' risk attitudes				By fathers' risk attitudes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Father's log real income	0.309***	0.291***								
	(0.057)	(0.054)								
Father's log real income * risk *averse* sons/fathers [A]			0.314***	0.153***	0.301***	0.320***	0.343***	0.218***	0.345***	0.349***
			(0.079)	(0.082)	(0.088)	(0.085)	(0.068)	(0.070)	(0.075)	(0.073)
Father's log real income * risk *taking* sons/fathers [A]			0.297***	0.211***	0.338***	0.329***	0.235**	0.124	0.277***	0.276***
			(0.075)	(0.074)	(0.079)	(0.076)	(0.094)	(0.093)	(0.098)	(0.095)
Risk taking son [A]			0.238	-0.375	-0.217	-0.002	0.779	0.665	0.461	0.496
			(0.853)	(0.831)	(0.814)	(0.787)	(0.932)	(0.900)	(0.882)	(0.851)
Son of risk taking father [A]			-0.085*	-0.088*	-0.087*	-0.092**	0.103**	0.085**	0.077**	0.072*
			(0.048)	0.046)	(0.045)	(0.043)	(0.040)	(0.039)	(0.038)	(0.037)
Son's years of education				0.038***	0.047***	0.064***		0.037***	0.046***	0.064***
				(0.007)	(0.007)	(0.008)		(0.007)	(0.007)	(0.008)
Father's years of education					-0.040***	-0.032***			-0.040***	-0.032***
					(0.010)	(0.009)			(0.010)	(0.009)
Son's firm tenure						0.010**				0.010**
						(0.004)				(0.004)
Son's years of experience						0.016***				0.017***
						(0.006)				(0.006)
Constant	5.488***	5.618***	5.409***	6.215***	5.380***	4.673***	5.187***	5.710***	5.038***	4.437***
	(0.453)	(0.428)	(0.624)	(0.621)	(0.640)	(0.638)	(0.537)	(0.528)	(0.542)	(0.542)
R-squared	0.088	0.075	0.097	0.162	0.200	0.258	0.099	0.163	0.201	0.259
N	305	365	365	365	365	365	365	365	365	365

Notes: The table reports coefficients from OLS regressions. The coefficients on the interaction terms indicate IGEs for the respective risk grouping of the column's headline. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. [A] Dummy variable. The resulting coefficient on the interaction term indicates the persistence in incomes for the respective risk grouping of the column's headline.

and fathers' education. The difference in IGE estimates remains considerable at 6.8 percentage points which persists in the final model of column 10, which further controls for individual labour market characteristics.

The results are robust to varying lifetime income definitions as can be seen from table 6. It reports the results for different requirements of minimum income observations over which the average is taken in approximating lifetime incomes.

TABLE 6 — ROBUSTNESS CHECKS, IGE COEFFICIENTS BY RISK ATTITUDES WITH VARYING LIFETIME INCOME DEFINITIONS

	More than one income observation		More than two income observations		More than three income observations		More than four income observations	
Sons	(1)[A]	(2)[B]	(3)[A]	(4)[B]	(5)[A]	(6)[B]	(7)[A]	(8)[B]
Risk	0.291***	0.307***	0.314***	0.320***	0.304***	0.294***	0.325***	0.307***
averse	(0.076)	(0.080)	(0.079)	(0.085)	(0.085)	(0.094)	(0.085)	(0.094)
Risk	0.335***	0.366***	0.297***	0.329***	0.273***	0.296***	0.314***	0.296***
taking	(0.074)	(0.073)	(0.075)	(0.076)	(0.079)	(0.083)	(0.093)	(0.094)
Fathers								
Risk	0.338***	0.349***	0.343***	0.349***	0.335***	0.329***	0.372***	0.351***
averse	(0.066)	(0.069)	(0.068)	(0.073)	(0.073)	(0.081)	(0.075)	(0.082)
Risk	0.268***	0.323***	0.235**	0.276***	0.201**	0.236**	0.186	0.164
taking	(0.092)	(0.091)	(0.094)	(0.095)	(0.098)	(0.101)	(0.120)	(0.121)
N	407	407	365	365	320	320	287	287

Notes: The table reports IGE coefficients from OLS regressions with varying numbers of minimum income observations to approximate lifetime incomes. The complete estimation results are reported in the appendix, table 16-18. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. [A] The model specification only includes family risk attitudes, where the reported IGE is the interaction term of fathers' log incomes with the respective dummy variable indicating risk group affiliation. [B] The model specification includes the full set of control variables, where the reported IGE is the interaction term of fathers' log incomes with the respective dummy variable indicating risk group affiliation.

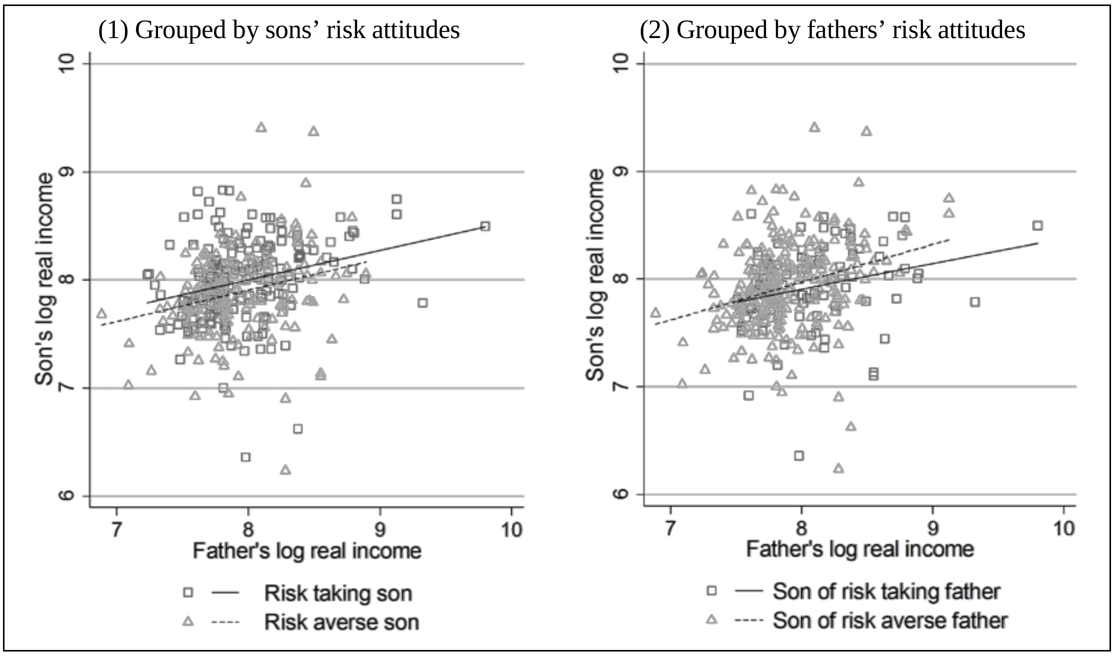


Figure 4 – Intergenerational persistence in incomes

To conclude, there is no sign of a difference in income mobility between sons with differing risk attitudes. However, there are persistent signs of higher income mobility for sons of risk taking fathers. This is illustrated in figure 4, plotting the IGE estimation results from column 3 and 7 of table 5.

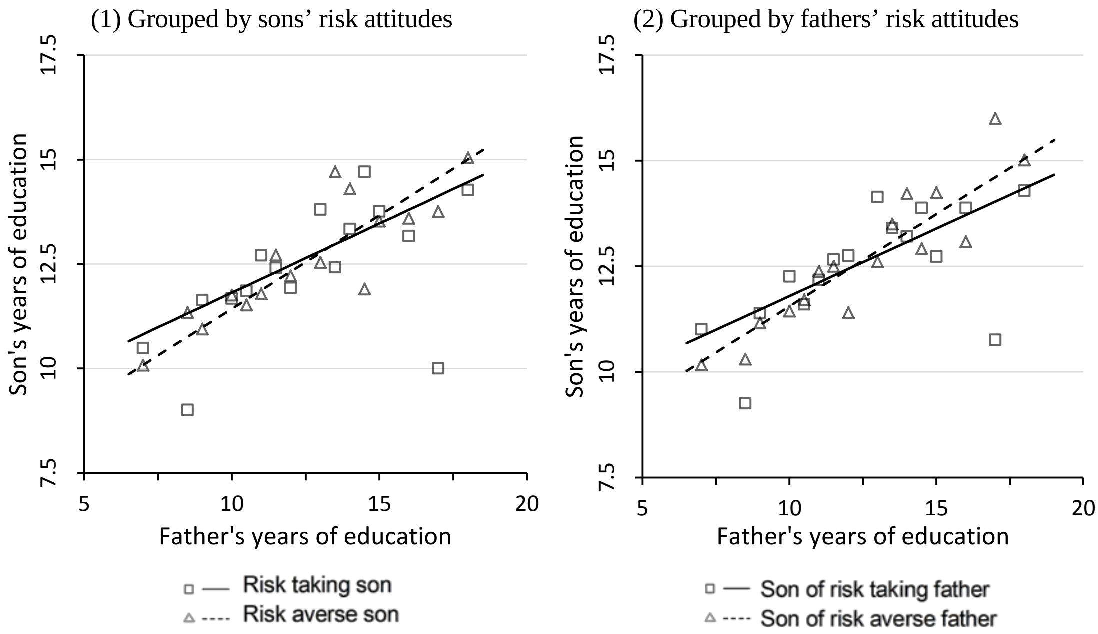
5.1.2 Intergenerational educational mobility by risk attitudes

The lower data requirements outlined allow for the analysis of educational mobility to be based on a larger sample, enabling more precise estimates. Table 7 presents the OLS estimation results of educational persistence across generations. Generally, one more year of paternal education is on average associated with sons having $0.389 * 12 = 4.7$ months more of education. As can be seen from column 2, this intergenerational link is smaller for risk taking sons and does not change when paternal risk attitudes are controlled for (column 3). A very similar difference can be observed for different paternal risk attitudes. Where the father takes more risk, one more year of paternal education is associated with $0.317 * 12 = 3.8$ months more education for the son, while it is $0.434 * 12 = 5.2$ months more education for sons of risk averse fathers (column 5). These group differences in educational mobility are statistically significant at 5 per cent. Figure 5 illustrates the findings.

TABLE 7 — INTERGENERATIONAL PERSISTENCE IN EDUCATION, DEPENDENT VARIABLE: SON'S YEARS OF EDUCATION

	By sons' risk attitudes			By fathers' risk attitudes	
	(1)	(2)	(3)	(4)	(5)
Father's years of education	0.389***				
	(0.029)				
Father's years of education * risk *averse* father/son [A]		0.447***	0.447***	0.437***	0.434***
		(0.040)	(0.040)	(0.039)	(0.039)
Father's years of education * risk *taking* father/son [A]		0.331***	0.332***	0.319***	0.317***
		(0.041)	(0.042)	(0.045)	(0.046)
Son of risk taking father [A]		1.544**	1.544**	1.426**	1.374*
		(0.651)	(0.652)	(0.706)	(0.709)
Risk taking son [A]			-0.009		0.215
			(0.159)		(0.142)
Constant	7.722***	6.961***	6.959***	7.182***	7.117***
	(0.326)	(0.440)	(0.441)	(0.422)	(0.423)
R-squared	0.144	0.149	0.149	0.147	0.149
N	1214	1214	1214	1214	1214

Notes: The table reports coefficients of OLS regressions. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. [A] Dummy variable. The coefficient indicates the persistence in educational attainment for the respective risk grouping of the column's headline.



Notes: The graphs plot regression results of son's years of education on father's years of education. The scatters show sons' mean educational attainment for each value of fathers' years of education.

Figure 5 – Intergenerational persistence in education.

The results are robust to various transformations of the risk variable. The patterns can also be confirmed for the attainment of a university degree, reported in table 8. The probability for risk taking sons holding a university degree is on average 19.3 percentage points higher when the father holds a university degree. This intergenerational association is 3.8 percentage points lower for risk taking sons than for risk averse sons, and 11.6 percentage point lower for sons of risk taking fathers compared to sons of risk averse fathers.

TABLE 8 — INTERGENERATIONAL PERSISTENCE IN UNIVERSITY DEGREES, DEP. VARIABLE: SON'S UNIVERSITY DEGREE

	By sons' risk attitudes			By fathers' risk attitudes	
	(1)	(2)	(3)	(4)	(5)
Father's university degree	0.193***				
	(0.034)				
Father's university degree * risk *averse* son/father[A]		0.214***	0.216***	0.247***	0.246***
		(0.053)	(0.053)	(0.048)	(0.049)
Father's university degree * risk *taking* son/father[A]		0.176***	0.178***	0.131***	0.130***
		(0.045)	(0.045)	(0.049)	(0.049)
Son of risk taking father[A]		0.020	0.022	0.016	0.013
		(0.022)	(0.022)	(0.025)	(0.025)
Risk taking son[A]			-0.011		0.015
			(0.024)		(0.022)
Constant	0.137***	0.127***	0.129***	0.132***	0.126***
	(0.011)	(0.015)	(0.015)	(0.013)	(0.015)
R-squared	0.038	0.039	0.039	0.042	0.042
N	1214	1214	1214	1214	1214

Notes: The table reports coefficients of OLS regressions. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. [A] Dummy variable. The coefficient indicates the persistence in educational attainment for the respective risk grouping of the column's headline.

Concluding this section, hypothesis 1 can be partly confirmed. Risk taking sons exhibit a higher educational mobility than risk averse sons. However, there are no consistent differences in income mobility between these groups. This suggests that own risk attitudes further impact incomes through channels other than education.

Sons of risk taking fathers are associated with greater educational mobility and higher income mobility. It is suggestive that higher educational mobility translates into higher income mobility through parental risk attitudes.

5.2 Risk attitudes and education in the transmission mechanism

This section focuses on the hypothesised link between risk attitudes and education. First, risk group differences in the level of educational attainments are analysed. Then, it is checked whether risk group heterogeneities in returns to education could justify varying levels of investment.

5.2.1 Risk attitudes and educational attainments

Multiple regression analysis is used to identify the link between family risk attitudes and educational attainments. In favour of informational variation in variables, the risk variable uses the standardised value of individuals' risk attitudes within their generation. The direct statistical associations between sons' educational attainments and family risk attitudes are plotted in figure 6. The relationship between sons' education and their fathers' risk attitudes seems more pronounced than the link between sons' education and their own risk attitudes. Sons with risk taking fathers seem to obtain higher levels of education, on average.

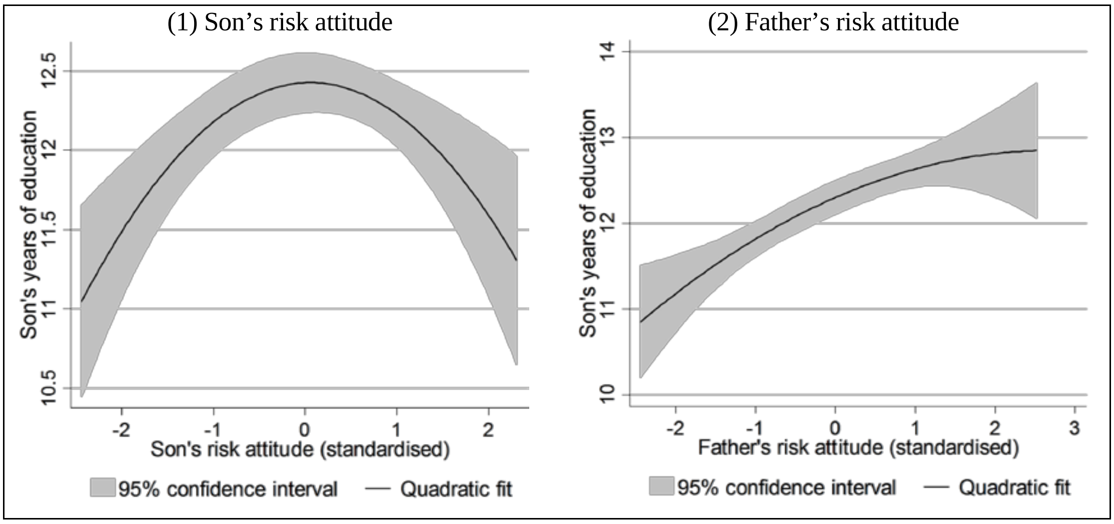


Figure 6 – Simple quadratic regression of sons' years of education on sons'/fathers' risk attitudes

Table 9 presents OLS estimation results with years of education as the dependent variable. The model of column 1 incorporates only measures of individual and paternal risk attitudes into the regression. There is no direct correlation between sons' risk attitudes and their years of education when paternal risk attitudes are controlled for. However, these paternal risk attitudes are highly correlated with sons' educational attainment, given sons risk attitudes. A one standard deviation higher risk attitude of fathers is associated with $0.726 * 12 = 8.7$ months more schooling of sons. The model in column 2 further controls for family background. The magnitude of the coefficient on the paternal risk attitude reduces to 0.344 but remains significant at 5 per cent. There is still the significant association that sons of fathers with a one standard deviation higher risk attitude have on average $0.344 * 12 = 4.1$ months more education. This association persists when the model additionally accounts for individual characteristics, as well as a time fixed effect.

This analysis is repeated in a linear probability model on the dependent variable "university degree", which takes the value one if the son graduated from university, zero otherwise. As can be seen from table 10, there is again a strong role for fathers' risk attitudes on sons' achievements of a university degree. This correlation reduces in magnitude when family background, individual characteristics and a time trend are controlled for, but remains significant with a p-value of 0.067.

TABLE 9 — DETERMINANTS OF SON'S YEARS OF EDUCATION

	(1)	(2)	(3)
Son's risk attitude [A]	-0.054	-0.003	0.008
	(0.163)	(0.144)	(0.147)
Father's risk attitude [A]	0.726***	0.344**	0.325**
	(0.146)	(0.135)	(0.136)
Father's years of education		0.546	0.473
		(0.417)	(0.416)
Father's years of education, squared		-0.008	-0.005
		(0.017)	(0.017)
Father with vocational training [B]		-0.157	-0.149
		(0.430)	(0.432)
Father with higher education [B]		1.050*	0.964
		(0.622)	(0.630)
Father with degree from university [B]		0.385	0.297
		(0.810)	(0.836)
Father's log real income		13.815	13.789
		(8.938)	(8.992)
Father's log real income, squared		-0.774	-0.775
		(0.555)	(0.557)
Son's health state			-0.183
			(0.255)
Son's height in cm			0.020
			(0.020)
Son's generation [C]			0.004
			(0.531)
Constant	12.788***	-53.182	-55.612
	(0.154)	(35.878)	(35.996)
R-squared	0.062	0.279	0.281
N	365	365	365

Notes: The table reports coefficients from OLS regressions. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. [A] The variable is standardised by generation. [B] Dummy variable. [C] Generation is a dummy variable taking the value one if the son is born in generation 3, zero if he is born in generation 2. No son was born in generation 1. This term accounts for time trends in educational attainments between generations.

The results of this section strongly suggest an at least indirect positive link between paternal risk attitudes and sons' educational attainments and supports hypothesis 2. Sons of risk taking fathers obtain higher levels of education, on average. This confirms previous pioneering findings of Brown *et al.* (2012) on the role of parental risk attitudes on education.

TABLE 10 — DETERMINANTS OF SON'S UNIVERSITY DEGREE

	(1)	(2)	(3)
Son's risk attitude [A]	-0.027	-0.022	-0.020
	(0.024)	(0.022)	(0.022)
Father's risk attitude [A]	0.096***	0.042*	0.040*
	(0.023)	(0.022)	(0.022)
Father's years of education		0.044	0.029
		(0.072)	(0.073)
Father's years of education, squared		-0.000	0.000
		(0.003)	(0.003)
Father with vocational training [B]		-0.025	-0.021
		(0.069)	(0.070)
Father with higher education [B]		0.166	0.148
		(0.103)	(0.103)
Father with degree from university [B]		0.045	0.035
		(0.145)	(0.150)
Father's log real income		0.727	0.753
		(0.994)	(1.005)
Father's log real income, squared		-0.030	-0.032
		(0.062)	(0.063)
Son's health state			-0.017
			(0.038)
Son's height in cm			0.004
			(0.003)
Son's generation [C]			-0.076
			(0.100)
Constant	0.297***	-4.067	-4.721
	(0.024)	(3.989)	(4.042)
R-squared	0.045	0.209	0.214
N	365	365	365

Notes: The table reports coefficients from OLS regressions. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. [A] The variable is standardised by generation. [B] Dummy variable. [C] Generation is a dummy variable taking the value one if the son is born in generation 3, zero if he is born in generation 2. No son was born in generation 1. This term accounts for time trends in educational attainments between generations.

5.2.2 Risk attitudes and returns to education

This section examines whether risk group differences in educational investments can be justified by heterogeneities in returns to education. The first approach applies an augmented version of Mincer's human capital earnings function (Altonji and Dunn, 1995). The results are presented in table 11. Column 1 serves as reference point and reports results for a homogenous returns to education model described in equation (10). The estimated average returns to every year of education are 7.5 per cent, which corroborates previous research on returns to education in Germany by Lauer and Steiner (2000) using the same data source. The model specifications of columns 2 and 3 account for group heterogeneity and include interaction terms indicating certain risk group affiliations, as outlined in equation (13). Risk taking sons on average receive 3.0 percentage point lower returns to education than their risk averse peers, given the risk attitude of their fathers. This effect is significant at a p-value of 0.022. As shown in column 3, sons of risk taking fathers receive 2.2 percentage point higher returns to education, holding their own risk attitudes constant. This difference in returns to education is significant at p= 0.084.

TABLE 11 — MINCER WAGE REGRESSION, DEPENDENT VARIABLE: SON'S MEAN LOG REAL INCOME

	(1)	(2)	(3)
Son's years of education	0.074***	0.088***	0.069***
	(0.010)	(0.011)	(0.011)
Son's age	0.548***	0.506**	0.559***
	(0.210)	(0.214)	(0.206)
Son's age, squared	-0.008***	-0.007**	-0.008***
	(0.003)	(0.003)	(0.003)
Son's firm tenure	0.001	0.001	0.001
	(0.013)	(0.013)	(0.013)
Son's firm tenure, squared	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Son's working experience	0.077***	0.077***	0.078***
	(0.018)	(0.018)	(0.018)
Son's working experience, squared	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
Son's health state	-0.078**	-0.084**	-0.077**
	(0.034)	(0.034)	(0.034)
Son's height in cm	0.005	0.005*	0.004
	(0.003)	(0.003)	(0.003)
Father's years of education	-0.010	-0.012	-0.010
	(0.011)	(0.011)	(0.011)
Risk taking son [A]	0.079**	0.468***	0.084**
	(0.038)	(0.168)	(0.038)
Risk taking father [A]	-0.078*	-0.086*	-0.367**
	(0.045)	(0.044)	(0.171)
Son's years of education *		-0.030**	
risk *taking* son [A]		(0.013)	
Son's years of education *			0.022*
risk *taking* father [A]			(0.013)
Constant	-3.658	-3.208	-3.774
	(3.632)	(3.697)	(3.569)
R-squared	0.287	0.299	0.292
N	365	365	365

Notes: The table reports coefficients from OLS estimations of Mincer wage regressions. Columns 2 and 3 include an interaction term of son's years of education and either son's or his father's risk attitude, indicating differences in returns to education by risk attitudes. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
[A] Dummy variable.

The obtained estimates are likely to be upward biased as the data do not allow controlling for individual ability. Dohmen *et al.* (2009) find a positive correlation of risk attitudes and cognitive ability. This would suggest an upward bias in the estimates of high risk individuals' returns to education. Though it has not been empirically tested, the positive intergenerational correlation of risk attitudes (Dohmen *et al.*, 2005) and the link between own risk attitudes and ability also suggests that the estimator for sons of risk taking fathers is contaminated with an upward bias.

The second approach therefore uses a family fixed effect model assuming that the fraction of unobserved ability that impacts educational attainments is a constant family ability component and the same for sons and fathers. Differencing sons and fathers characteristics leads to the cancellation of the relevant unobserved components, as illustrated in equation (16).[12] The sample size reduces to 313 due to limited data availability on the parental generation. Table 11 presents the estimation results. The baseline estimate is again 7.5 per cent. The coefficient on the interaction term in column 2 indicates no significant differences in returns to education by sons' risk attitudes. However, sons of risk taking fathers are again found to earn higher returns to education, on average 1.8 percentage points. Each additional year of education is rewarded by 8.8 percentage points higher incomes, ceteris paribus, if sons have risk taking fathers, compared to 7.0 percentage points for sons with risk averse fathers. The result for differences by paternal risk attitudes is close to the findings of the Mincer wage regressions. However, the coefficient is imprecisely estimated.

[12] If educational choices are related to individual specific ability components rather than the assumed family specific ability components, estimates of returns to education of this fixed-effect model can exhibit stronger upward biases than Mincer wage regressions which omit control variables for ability (Altonji and Dunn, 1995).

TABLE 12 — FAMILY FIXED EFFECT MODEL, DEPENDENT VARIABLE: Δ MEAN LOG REAL INCOME

	(1)	(2)	(3)
Δ education	0.075***	0.078***	0.070***
	(0.009)	(0.013)	(0.011)
Δ age	-0.098**	-0.100**	-0.102**
	(0.042)	(0.043)	(0.043)
Δ age, squared	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)
Δ tenure	0.014	0.015	0.014
	(0.014)	(0.014)	(0.014)
Δ tenure, squared	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
Δ experience	0.057***	0.055***	0.055***
	(0.009)	(0.010)	(0.010)
Δ experience, squared	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Δ health state	-0.076**	-0.071**	-0.068**
	(0.035)	(0.035)	(0.035)
Δ height	0.006*	0.006*	0.006*
	(0.003)	(0.003)	(0.003)
Δ risk attitudes [B]	0.100***	0.176***	0.043
	(0.038)	(0.053)	(0.046)
Δ education *		-0.004	
risk *taking* son [A]		(0.016)	
Risk taking son [A]		-0.128*	
		(0.068)	
Δ education *			0.018
risk *taking* father [A]			(0.016)
Risk taking father [A]			-0.158**
			(0.067)
Constant	-0.210*	-0.168	-0.160
	(0.114)	(0.123)	(0.121)
R-squared	0.340	0.350	0.352
N	313	313	313

Notes: The table reports coefficients from OLS estimations of a family fixed effect model. Δ indicates the difference between son's and father's respective characteristic. Columns 2 and 3 include an interaction term of son's years of education and either son's or his father's risk attitude, indicating differences in returns to education by risk attitudes. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. [A] Dummy variable. [B] Son's and father's risk attitudes entered as dummy variables.

In order to check for robustness of these results, the analysis has been repeated for varying definitions of risk attitudes. Further, it was checked whether similar patterns arise on returns to a university degree. Results can be compared in table 13. Though these estimates are often imprecise, there are signs of lower returns to education for risk taking sons compared to risk averse sons across models, varying definitions of the risk variable and different measures of school achievements. Further, one can observe persistently higher returns to education for sons of risk taking fathers compared to sons of risk averse fathers.

TABLE 13 — ROBUSTNESS CHECKS FOR DIFFERENCES IN RETURNS TO EDUCATION

Interaction of	Mincer wage regression			Family fixed effect model		
Years of education	Dummy[A]	Standardised[B]	Original[C]	Dummy[A]	Standardised[B]	Original[C]
* son's	-0.030**	-0.006	-0.003	-0.004	-0.005	-0.002
risk attitudes	(0.013)	(0.006)	(0.003)	(0.016)	(0.007)	(0.003)
* father's	0.022*	0.008	0.003	0.018	0.018**	0.006**
risk attitudes	(0.013)	(0.005)	(0.002)	(0.016)	(0.008)	(0.003)
University degree						
* son's	-0.174**	-0.025	-0.011	-0.112	-0.053	-0.024
risk attitudes	(0.087)	(0.046)	(0.021)	(0.094)	(0.051)	(0.024)
* father's	0.076	0.056	0.017	0.020	0.081*	0.027
risk attitudes	(0.088)	(0.037)	(0.015)	(0.092)	(0.048)	(0.019)
N	365	365	365	313	313	313

Notes: The table reports the differences in returns to education and to a university degree by risk attitudes of sons and fathers, estimated by OLS Mincer wage regressions and a family fixed effect models. The reported coefficients are the coefficients on interaction terms of education and risk attitudes using the same control variables as in the specifications of table 11 and 12. Variables indicating educational achievements are years of education and a dummy variable indicating whether holding of a university degree respectively. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. [A] This model uses a dummy variable indicating the son's own or his father's risk attitude, taking the value one if the respective individual is risk taking. [B] This model uses the reported risk attitude standardised by generation with mean zero and a standard deviation of one. [C] This model uses the originally reported risk attitude measured on a scale from zero (fully risk averse) to ten (fully risk taking).

Summarising this section, there is no differences in education levels between risk taking and risk averse sons. Seemingly, risk taking sons earn lower returns to education compared to more risk averse peers supporting the prior belief of a complex relationship between own risk attitudes and its effect on incomes and income mobility.

Sons with risk taking fathers achieve higher levels of education. There is also modest evidence of higher returns to education for these sons which complements the previous finding in that economic theory predicts higher investments in an asset when returns to investments are higher, ceteris paribus (Kocherlakota, 1996).

6 Discussion and limitations

The study analysed the role of family risk attitudes in intergenerational educational and income mobility using 1984-2009 data of father-son pairs from Germany. The first research hypothesis suggested higher educational and income mobility for risk taking sons and for sons of risk taking fathers. There is significant evidence suggesting this to hold for education. The relationship between risk attitudes and income mobility requires the distinction between fathers' and sons' attitudes.

There is modest evidence suggesting that intergenerational income mobility is higher for sons of risk taking fathers. This confirms the suggested transmission mechanism with education as important moderator of income mobility. As sons of risk taking fathers exhibit a lower educational similarity to their fathers, a lower resemblance of their lifetime incomes is not surprising when education is an important determinant of incomes. This also suggests that paternal risk attitudes do not severely impede sons' earnings capacities through other channels which could erase the positive effect of higher educational mobility on income mobility.

For risk taking sons, however, the above mentioned higher educational mobility does not seem to transmit into higher income mobility. There is no consistent difference in income mobility compared to risk averse peers, which is surprising given research by Budría *et al.* (2009), who find that personal risk attitudes positively impact wage growth. This suggests that the relationship between own risk attitudes and income mobility is more complex and does not operate through wage growth and education alone. It is, for example, conceivable that a weaker labour market attachment of risk taking sons has erasing effects. They could change jobs more frequently and receive lower returns to tenure. They could also be more frequently out of employment, which could lead to lower levels of experience, resulting in wage discounts. An alternative explanation could be found in the sample selection. Intergenerational income elasticities and education correlations only measure the degree of similarity between generations, but are not conclusive about upward or downward mobility. If sons with high risk attitudes experience a higher probability of unemployment and are more downward mobile, they are less likely to be member of the sample which would result in a sample selection bias and over-represent father-son pairs with full participation in the labour market. This could diminish risk group differences in income mobility. For a better understanding of the role of sons' risk attitudes in the transmission mechanism, further research on the relationship between risk attitudes and other labour market characteristics, such as varying labour market attachments and heterogeneities in returns to experience and tenure, is required.

The above analysis of income mobility is limited in that it exclusively comments on intergenerational similarities. An analysis of risk groups' differences in their ability to move through the overall earnings distribution, as suggested by Bhattacharya and Mazumder (2011), could provide further insights of the role of risk attitudes in the intergenerational transmission of incomes.

The second part of the analysis concentrated on education in the transmission process. I hypothesised that educational choices are impacted by parental risk attitudes rather than own risk attitudes as they are made at early stages in life and are associated with great uncertainty. In order to increase their information set, children consult their parents for advice on their investments in human capital. This parental advice incorporates parental risk attitudes. Consequently, children of risk taking parents heeding their advice obtain higher levels of education than children of risk averse parents. This builds a complete link between family background and offspring economic success.

This hypothesis is supported by the empirical findings. There is considerable evidence that sons of risk taking fathers obtain higher levels of education on average. Theory suggests that investments are higher where returns to investment are higher, ceteris paribus. This is in line with modest evidence of higher returns to education for sons with risk taking fathers[13]. This result has not yet received much attention in the economic literature and is in line with the first contribution by Brown *et al.* (2012). As direct data on individuals' risk attitudes are rare, empirical work testing the relationship between risk attitudes and education is scarce and identifies only a small role for own risk attitudes. Belzil and Leonardi (2007), for example, show that they have a small impact on education levels, which is surprising given the important role assigned to individuals' risk attitudes as determinant of human capital investments in the theoretical literature. The analysis of Belzil and Leonardi has not accounted for parental risk attitudes. Therefore, it is even conceivable that the identified modest role arises through a positive correlation with parental risk attitudes (Dohmen *et al.*, 2005).

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[13] This interpretation can be inverted and implies lower returns to education for sons of risk averse fathers. This could result from an underinvestment in education of this group and nonlinearities in returns to education, as identified by Trostel (2005).

The findings of this study contribute to the understanding of the transmission mechanism of income mobility and provide an intergenerational link between family risk attitudes and offspring economic outcomes. As data on risk attitudes become progressively available in other countries, they provide interesting scope for further empirical tests of my hypothesis. It could be extended and tested on both mothers' and fathers' risk attitudes. This could provide more robustness and give rise to a reassessment of the theoretical literature on investments in human capital and the impact of risk attitudes on it.

The findings also have important implications for economic inequality. If risk averse parents tend to exhibit lower abilities, lower educational levels and lower incomes, comparably lower investments in human capital would be recommended to children from socially weaker backgrounds. Parental risk aversion could lead to investments below the individual's optimal level. Underinvestment in education from deprived backgrounds can increase social inequality and prevent the income distribution from convergence to its mean income.

If the suggested link substantiates in future research, policy makers must be aware of the role of parental risk attitudes in designing policies favouring education equality. As returns to education are determined in the labour market, policy makers would have to alter the parental perception of human capital investment risks. For example, family background dependent grants for university attendance could considerably reduce parents' perceived risk of children's educational investments. Future research could evaluate comparable initiatives'[14] impact on these parental risk perceptions.

The discussion is closed with comments on limitations of the analysis. As mentioned earlier, the econometric strategy is constrained in identifying the *causal* effects of risk attitudes on economic mobility, education and labour market outcomes. There remains the possibility that findings are moderated by inconsistencies arising through measurement errors and omitted variables.

Differences in group elasticities could arise through varying magnitudes of measurement errors and lifecycle bias. Abstracting from the role of lifecycle bias, higher transitory fluctuations from lifetime incomes in reported incomes of fathers with higher risk attitudes could stronger attenuate IGE of the group of sons with high risk

[14] The German Government launched a broad scholarship programme in August 2010 for gifted children from all backgrounds for non-refundable support of 300 EUR on subsistence expenses during university education.

attitude fathers. Indeed, the literature suggests higher income volatility for individuals with higher risk attitudes (Budría *et al.*, 2009, Shore, 2011). However, there is no simple mean to evaluate the magnitude of differences in transitory fluctuations in incomes. Abstracting from measurement errors, one could also falsely identify differences in income elasticities by the risk attitude of sons' fathers if the parameters μ_a and θ_a of the lifecycle bias presented in equation (9) vary not only by age but also by ability (Pfeiffer and Eisenhauer, 2008). For example, with a steeper income growth path for sons with high cognitive ability, μ_a^{high} would be smaller than μ_a^{low} in early years of sons labour market experience. Through the intergenerational similarity of risk attitudes and their link to ability, this could have been introduced by a stronger attenuation of the estimated IGE for sons of risk taking fathers. As there is no complete earnings history which would provide certainty about the magnitude of the coefficients μ_a^{high} and μ_a^{low}, no reliable test could provide certainty about the impact of lifecycle biases.

A positive relationship between risk attitudes and cognitive ability could bias estimates on heterogeneous returns to education upwards when higher ability is associated with higher incomes. Accordingly, the returns for sons with higher risk attitudes would be overestimated and in fact be more negative than suggested. If the group of sons with high risk attitude fathers also exhibits higher ability, the premium for this group would be smaller than suggested. The effect should reduce in the family fixed effect model, which indeed is the case. The magnitude of any remaining ability bias cannot be assessed due to the lack of knowledge about individuals' actual ability.

Finally, the external validity of these findings is constrained by the restrictive sample selection which prevents from a balanced representation of the German population. However, this was never the objective of the analysis.

7 Conclusion

The intergenerational transmission of socio-economic status is of long-lasting interest for economists to better understand the dynamics of economic inequality and societies' equality of opportunities. While the early literature focused on the correct measurement of the intergenerational persistence in economic status, recent work has concentrated on revealing the underlying transmission mechanism, in which education was found to be an important mediator. As data on individuals' traits and attitudes become progressively available, research moves towards their role in the transmission process. Many economic decisions are impacted by risk attitudes. They were found to be highly correlated between generations and could play a significant role in the intergenerational transmission of economic status. However, this aspect has received little attention in the theoretical and empirical literature so far.

Based on 1984-2009 data on father-son pairs from the German Socio-Economic Panel Survey and a unique additional survey on their risk attitudes, this study analyses the role of family risk attitudes in education and intergenerational mobility.

The findings suggest a complex relationship between own risk attitudes and income mobility. While risk taking sons have a higher educational mobility than risk averse sons, there is no difference in income mobility between these groups. Sons' risk attitudes do not considerably impact their levels of education, though risk taking sons seem to earn lower returns to education.

The risk attitude of sons' fathers provides a clearer picture on its impact on intergenerational mobility. Sons with risk taking fathers experience higher educational and suggestively higher income mobility. They obtain higher levels of education and modest evidence suggests that they earn higher returns to education.

The findings add to the understanding of the transmission mechanism of economic status between generations and suggest an important intergenerational link between parental risk attitudes and children's investment in human capital that has not received much attention in empirical or theoretical work. As results of this study only point to statistical rather than causal relationships, various suggested directions for future research could substantiate the findings. This could give rise for a reassessment of the role of risk attitudes in human capital investments and have important implications for public policy.

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Appendix

Tables

TABLE 14 — IGE ESTIMATIONS SEPARATELY BY FATHERS' RISK ATTITUDES, DEPENDENT VARIABLE: SON'S MEAN LOG REAL INCOME

	Simple model specification[B]		Full model specification[C]	
	Sons of risk *averse* fathers	Sons of risk *taking* fathers	Sons of risk *averse* fathers	Sons of risk *taking* fathers
	(1)	(2)	(3)	(4)
Father's log real income	0.343***	0.235**	0.352***	0.312***
	(0.068)	(0.097)	(0.077)	(0.112)
Risk taking son [A]	0.116**	0.062	0.091**	-0.021
	(0.046)	(0.083)	(0.043)	(0.071)
Son's years of education			0.054***	0.107***
			(0.009)	(0.017)
Father's years of education			-0.030***	-0.043**
			(0.011)	(0.017)
Son's firm tenure			0.010**	0.008
			(0.005)	(0.009)
Son's years of experience			0.011*	0.046***
			(0.007)	(0.013)
Constant	5.189***	5.977***	4.560***	3.975***
	(0.533)	(0.786)	(0.564)	(0.837)
R-squared	0.110	0.071	0.236	0.403
N	275	90	275	90

Notes: The table reports coefficients from OLS regressions of son's log income on father's log income, separately for risk averse/risk taking sons and sons of risk averse and risk taking fathers, respectively. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. [A] Dummy variable. [B] The model includes only controls for sons' own risk attitudes.

TABLE 15 — IGE ESTIMATIONS SEPARATELY BY SONS' RISK ATTITUDES, DEPENDENT VARIABLE: SON'S MEAN LOG REAL INCOME

	Simple model specification[B]		Full model specification[C]	
	Risk *averse* sons	Risk *taking* sons	Risk *averse* sons	Risk *taking* sons
	(1)	(2)	(3)	(4)
Father's log real income	0.306***	0.305***	0.241***	0.406***
	(0.080)	(0.077)	(0.089)	(0.094)
Son of	-0.054	-0.112*	-0.059	-0.139**
risk taking father [A]	(0.070)	(0.065)	(0.061)	(0.063)
Son's years of education			0.082***	0.048***
			(0.011)	(0.013)
Father's years of education			-0.034***	-0.036**
			(0.012)	(0.015)
Son's firm tenure			0.012**	0.003
			(0.005)	(0.007)
Son's years of experience			0.015**	0.023**
			(0.007)	(0.010)
Constant	5.471***	5.595***	5.093***	4.310***
	(0.631)	(0.606)	(0.641)	(0.701)
R-squared	0.070	0.091	0.324	0.192
N	197	168	197	168

Notes: The table reports coefficients from OLS regressions of son's log income on father's log income, separately for risk averse/risk taking sons and sons of risk averse and risk taking fathers, respectively. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. [A] Dummy variable. [B] The model includes only controls for fathers' risk attitudes

TABLE 16 — IGE ESTIMATION WITH LIFETIME INCOMES APPROXIMATED BY AVERAGING MORE THAN *ONE* INCOME OBSERVATION, DEPENDENT VARIABLE: SON'S MEAN LOG REAL INCOME

	By son's risk attitude		By father's risk attitude	
	(1)	(2)	(3)	(4)
Father's log real income * risk	0.291***	0.307***	0.338***	0.349***
averse sons/fathers [A]	(0.076)	(0.080)	(0.066)	(0.069)
Father's log real income * risk	0.335***	0.366***	0.268***	0.323***
taking sons/fathers [A]	(0.074)	(0.073)	(0.092)	(0.091)
Risk taking son [A]	-0.236	-0.379	0.110***	0.086**
	(0.830)	(0.753)	(0.039)	(0.035)
Son of	-0.058	-0.075*	0.501	0.132
risk taking father [A]	(0.046)	(0.042)	(0.907)	(0.818)
Son's years of education		0.069***		0.068***
		(0.008)		(0.008)
Father's years of education		-0.037***		-0.037***
		(0.009)		(0.009)
Son's firm tenure		0.010**		0.010**
		(0.004)		(0.004)
Son's years of experience		0.020***		0.020***
		(0.005)		(0.005)
Constant	5.562***	4.703***	5.195***	4.380***
	(0.602)	(0.600)	(0.523)	(0.514)
R-squared	0.100	0.281	0.101	0.281
N	407	407	407	407

Notes: The table reports coefficients from OLS regressions. The coefficients on the interaction terms indicate IGEs for the respective risk grouping of the column's headline. Standard errors are reported in parentheses.
* p<0.10, ** p<0.05, *** p<0.01. [A] Dummy variable. The resulting coefficient on the interaction term indicates the persistence in incomes for the respective risk grouping of the column's headline.

TABLE 17 — IGE ESTIMATION WITH LIFETIME INCOMES APPROXIMATED BY AVERAGING MORE THAN *THREE* INCOME OBSERVATIONS, DEPENDENT VARIABLE: SON'S MEAN LOG REAL INCOME

	By son's risk attitude		By father's risk attitude	
	(1)	(2)	(3)	(4)
Father's log real income * risk	0.304***	0.294***	0.335***	0.329***
averse sons/fathers [A]	(0.085)	(0.094)	(0.073)	(0.081)
Father's log real income * risk	0.273***	0.296***	0.201**	0.236**
taking sons/fathers [A]	(0.079)	(0.083)	(0.098)	(0.101)
Risk taking son [A]	0.368	0.077	0.127***	0.096**
	(0.908)	(0.844)	(0.043)	(0.040)
Son of	-0.097*	-0.107**	0.984	0.636
risk taking father [A]	(0.051)	(0.047)	(0.983)	(0.904)
Son's years of education		0.069***		0.069***
		(0.009)		(0.009)
Father's years of education		-0.034***		-0.034***
		(0.011)		(0.011)
Son's firm tenure		0.010**		0.010**
		(0.004)		(0.004)
Son's years of experience		0.013**		0.013**
		(0.006)		(0.006)
Constant	5.504***	4.866***	5.254***	4.593***
	(0.667)	(0.706)	(0.575)	(0.609)
R-squared	0.100	0.252	0.104	0.254
N	320	320	320	320

Notes: The table reports coefficients from OLS regressions. The coefficients on the interaction terms indicate IGEs for the respective risk grouping of the column's headline. Standard errors are reported in parentheses.
* p<0.10, ** p<0.05, *** p<0.01. [A] Dummy variable. The resulting coefficient on the interaction term indicates the persistence in incomes for the respective risk grouping of the column's headline.

TABLE 18 — IGE ESTIMATION WITH LIFETIME INCOMES APPROXIMATED BY AVERAGING MORE THAN *FOUR* INCOME OBSERVATIONS, DEPENDENT VARIABLE: SON'S MEAN LOG REAL INCOME

	By son's risk attitude		By father's risk attitude	
	(1)	(2)	(3)	(4)
Father's log real income * risk	0.325***	0.307***	0.372***	0.351***
averse sons/fathers [A]	(0.085)	(0.094)	(0.075)	(0.082)
Father's log real income * risk	0.314***	0.296***	0.186	0.164
taking sons/fathers [A]	(0.093)	(0.094)	(0.120)	(0.121)
Risk taking son [A]	0.190	0.163	0.100**	0.073*
	(0.989)	(0.916)	(0.044)	(0.041)
Son of	-0.094*	-0.102**	1.399	1.391
risk taking father [A]	(0.052)	(0.048)	(1.134)	(1.043)
Son's years of education		0.068***		0.069***
		(0.010)		(0.010)
Father's years of education		-0.028**		-0.027**
		(0.011)		(0.011)
Son's firm tenure		0.011**		0.011**
		(0.004)		(0.004)
Son's years of experience		0.013*		0.013*
		(0.007)		(0.007)
Constant	5.369***	4.721***	4.997***	4.365***
	(0.671)	(0.717)	0.587	0.623
R-squared	0.103	0.253	0.108	0.259
N	287	287	287	287

Notes: The table reports coefficients from OLS regressions. The coefficients on the interaction terms indicate IGEs for the respective risk grouping of the column's headline. Standard errors are reported in parentheses.
* p<0.10, ** p<0.05, *** p<0.01. [A] Dummy variable. The resulting coefficient on the interaction term indicates the persistence in incomes for the respective risk grouping of the column's headline.