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The Causal Effect of Education on Health:

A CONSIDERATION OF METHODOLOGICAL CHALLENGES, MEDIATING EFFECTS, AND VARIATION BY AGE

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Bamberg, September 2021

Jacqueline Kroh

Content

Chapter 1 – The causal effect of education on health: Introduction and overview

1 Introduction

Education, defined as the process of moral, mental, and cognitive development through teaching and training (Smith, 1995), is beneficial to an individual's life. Education enables access to valuable resources as it supplies individuals' with skills and competencies, provides differentiated signals of individuals' productivity levels and personal characteristics, and defines social status and position in society. Education is, for instance, linked to better labor market positions, higher income, or better social integration (Afzal, 2011; Lochner, 2011; Psacharopoulos and Patrinos, 2018). In addition, education is generally regarded to be a prerequisite for individuals' health and wellbeing (Mackenbach, 2012; Michalos, 2008; Murtin et al., 2017). Thus, a lack of education can be expected to have far-reaching consequences on an individual's life outcomes.

Because of education's prominence in individual development, there exists a wide range of literature investigating the so-called private returns to education in order to obtain deeper insights into the individual benefits of education and the consequences of the lack thereof. In particular, studies examine the causal effects of education on labor market returns (e.g. Harmon et al., 2003), social integration and political participation (e.g. Bömmel and Heineck, 2020; Lochner, 2011), as well as health and wellbeing (e.g. Galama et al., 2018; Oreopoulos, 2007), since observed associations do not necessarily implicate a causal effect of education on these outcomes. For instance, confounding factors may result in a spurious correlation between the two, while reversed causal relationships could explain these links (Card, 1999; Elwert and Winship, 2014). Thus, utilizing different methods, social scientists have attempted to obtain causal estimates on monetary and non-monetary outcomes (e.g. Galama et al., 2018; Harmon et al., 2003; Lochner, 2011). However, empirical evidence is far from conclusive. While most studies highlight a causal effect of education on income (Ashenfelter et al., 1999), the causal effect of education on non-monetary outcomes, such as social integration and political participation, or health and wellbeing, is still under discussion (Hamad et al., 2018; Huang et al., 2009; Lochner, 2011; Oreopoulos, 2007). Thus, it is unclear to which extent education contributes to individuals' lives.

There is substantial evidence in literature indicating that individuals with lower levels of education show significantly lower levels of life expectancy (Mackenbach, 2012; Murtin et al., 2017), are more than twice as likely to suffer from cardiovascular disease, diabetes or asthma, are more likely to become mentally ill, and show higher levels of functional limitations and disabilities (Mackenbach, 2006). Since this seems to suggest a causal link between education and health, identifying relevant mechanisms and dimensions of education could highlight valuable strategies to foster individuals' health-related quality of life. In addition, it could facilitate the political identification of strategies to decrease (health-related) social costs, increase the overall level of economic productivity, and argue for higher investments in education (Healy, 2006; Mackenbach et al., 2011). Thus, it is crucial to find clear evidence of the causal relationship between education and health, the relevant causal mechanisms, and the impact of different functions of education.

Although there already exists a wide range of literature demonstrating that an individual's education is associated with overall health status, physical and mental health, daily functioning, and longevity (Furnée et al., 2008; Xue et al., 2021), empirical evidence of the causality of this link remains ambiguous (Galama et al., 2018; Hamad et al., 2018; Xue et al., 2021). Due to different operationalizations of health, the high variation of methods used, different populations studied, and the historical and political context investigated, empirical studies show diversity in the existence, direction, and size of causal effects (Galama et al., 2018; Hamad et al., 2019; Zajacova and Lawrence, 2018). Thus, although much work on this subject has been done in recent decades, the available evidence to date is limited in substantiating that investing in education is the best long-term strategy for improving individual health.

Another unanswered question relevant to understanding the effect of education on health is how different functions of education affect individuals' health. Theoretically, education should show divergent effects on health depending on the function of education addressed. On the one hand, higher skills and competence levels should increase health since they enable more efficient investments in health, increase the productivity in the labor-market-related and non-market related sector, and, thus, result in higher levels of resources available for investments in health (Grossman, 2006). In addition, better skills and higher knowledge levels increase individuals' feelings of competence and, consequently, contribute to the quantity of inherent psychological resources, such as self-esteem, self-perceived efficacy, mastery, and control (Ryan and Deci, 2000). On the other hand, outward signals of education (such as grades and certificates) and the defined social position provided by education should further affect individuals' health, because regardless of actual levels of skills and competencies, both determine access to labor-market related and non-market related resources (Spence, 1974; van de Werfhorst, 2011). They also provide competency-based feedback affecting individual self-esteem, self-perceived efficacy, and feelings of mastery and control (Ryan and Deci, 2000). Thus, independently of the skills and competencies acquired in educational settings, the credentials earned in education likely contribute to individuals' health. However, it is empirically unclear to which extent higher skills and competence levels, the provided signals, and social positions based on education make such a contribution. The majority of empirical studies investigating the causal effect of education on health primarily focuses either on years of schooling or educational certificates, both of which do not allow comparison between the different effects on health (Galama et al., 2018; Zajacova and Lawrence, 2018). As a result, there has been little analysis of how education affects health by its functions of enhancing individuals' skills and knowledge, and of providing an outward signal and status symbol.

These limitations also apply to the understanding of the causal mechanisms between education and health. Education is assumed to have an impact on health by improving individual resources that are beneficial for health, such as (health-related) knowledge and skills, occupational status, monetary resources, and social or psychological resources (for an overview see for example Cutler and Lleras-Muney, 2006; Ross and Wu, 1995). However, empirically, it is unclear whether all of these theoretically relevant mechanisms also show mediation effects in practice (Zajacova and Lawrence, 2018). While empirical research suggests indirect effects of education on health by individuals' occupational status and income, it is unclear whether education's effect on health is mediated by individuals' social or psychological resources. Empirical studies only find limited evidence for the contribution of these factors to the effect of education on health (e.g. Antonucci et al., 2003; Gallo et al., 2007; Sheikh et al., 2017; Vonneilich et al., 2012; Yang et al., 2019), and the small number of studies and their methodological and data-based limitations raise concerns about the validity of their results. Therefore, although various theoretical arguments point to (health-related) knowledge and skills, occupational status, monetary resources, and social or psychological resources as potential mechanisms, empirical falsification of their significance has been partially lacking.

For this reason, this dissertation project investigates private health returns to education, aiming to contribute to the wide range of literature that constitutes education as an important determinant of individuals' health (Grossman, 2000; Link and Phelan, 1995; Ross and Wu, 1995), and referring to a large number of studies, which show impressive differences in individuals' health by education levels. In doing so, this thesis adds to the ongoing discussion of the causal effect of education on health, the important mechanisms, and the relevance of different functions of education (Cutler and Lleras-Muney, 2006; Galama et al., 2018; Hamad et al., 2018; Xue et al., 2021). Thus, this thesis inserts itself into the debate on educational inequalities as an important dimension of individuals' life.

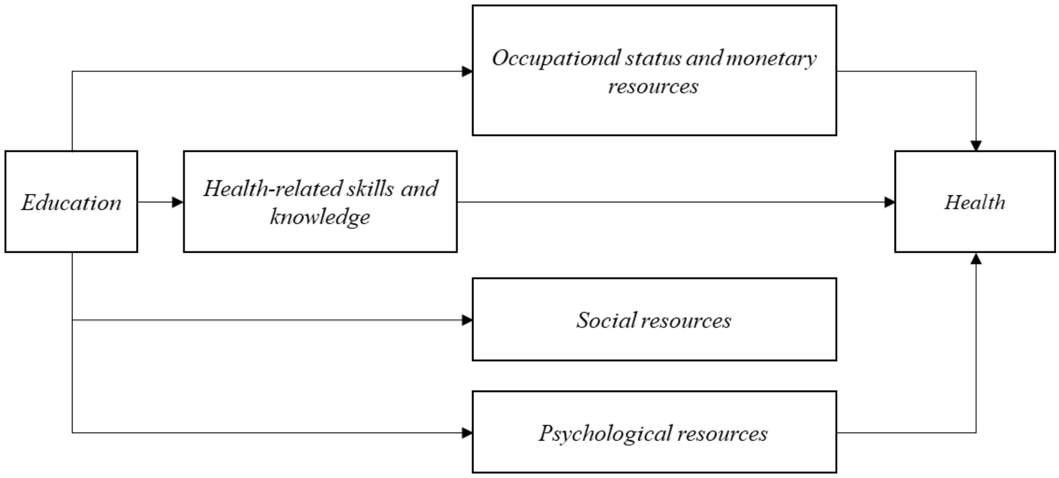
Referring to the aforementioned research gaps and unanswered questions, this thesis firstly aims to address the variation of the existence, size, and direction of the effect by addressing methodological challenges and variation by age. Thus, I ask the following research question: *"Does education positively affect individuals' health?",* complementing the existing literature by using health measurements and designs comparable to those employed in prior research in order to show the causality in different populations and contexts. In doing so, I target different age groups and the variation of the effect given by the empirical strategy employed. For example, I examine how education affects health at younger ages because childhood and adolescence set the fundaments for later life, but also investigate whether the effect of education on health is equally observable in higher age groups. Furthermore, I develop a more sophisticated strategy for estimating the causal effect of education on health in a quasi-experimental design to obtain deeper insights into causes of the variation in prior empirical results. Secondly, closely related to the first research question, this thesis examines how different aspects of education affect individual health. In doing so, I concentrate on the research question *"Do skills and knowledge levels and the signals of education positively affect individuals' (mental) health, and are these two different facets interrelated?"* By focusing on children and adolescents, I aim to shed more light on the relevance of education's different functions within the education-health relationship. Finally, this thesis aims to complement the scarce literature about the mediation of social resources in the effect of education on health. In particular, the following research question will be addressed: *"Do social relationships mediate the effect of education on health?"* I therefore contribute to the previous literature by implementing a causal mediation analysis and testing for the relevance of unobserved heterogeneity in a separate robustness check. Taken together, this dissertation addresses three main research questions related to the effect of education on health.

The thesis comprises four thematic chapters. Beginning with an overview of the topic, Chapter 1 briefly summarizes the theories guiding my research agenda. It highlights the theoretical arguments, suggesting a causal effect of education on health, and describes the related mechanisms. In addition, the chapter briefly summarizes the arguments of how the effects of education on health diverge across the life span. Furthermore, Chapter 1 presents the discussion of selection processes underlying the non-causal part of the association between education and health. It also describes the state of research, highlights the existing evidence and limitations, and offers more detailed information about the contribution this thesis makes to existing research. In doing so, the chapter concentrates on the empirical literature related to the main questions of this thesis. It also briefly describes the research agenda, addresses the data sets used, presents the operationalization of education and health, and describes the methods employed to identify the causal effect of education on health and the mediating effect through social relationships. Chapter 1 closes with a final summary, a critical discussion of the results, and an outlook. Chapters 2 to 4 constitute the main part of the thesis. Chapter 2 presents the empirical study regarding the effect of different aspects of education on health by concentrating on children, while chapter 3 offers analyses of the education-health relationship for working-age adults and provides deeper insights into the mediation effects of social relationships. Finally, chapter 4 presents empirical results of the investigation of education’s causal effect on health, which focus on health differences based on exogenous variation in years of education in older adults.

2 The causal effect of education on health

The following section sketches the theoretical background for a discussion of education's effects on health and presents the main arguments underlying the empirical investigations. I provide a definition of the main concepts, show why education should be a cause of better health, and argue for the principal mechanisms based on different theoretical approaches (see Figure 1 for an overview). In addition, I outline possible differences in the effect of education on health at different stages of the life course. Finally, I briefly state theoretical counterarguments against an effect of education on health taking into account reverse causality and confounding factors.

Figure 1: Overview of the Causal Mechanisms Linking Education to Health



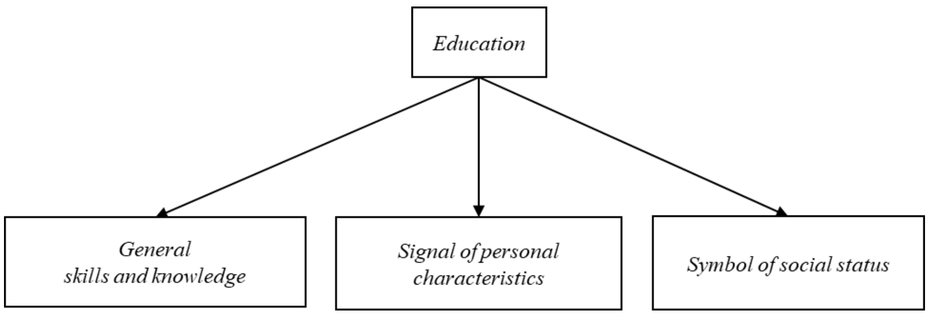
Source: Own illustration.
Note: For the sake of clarity, interdependencies between the mechanisms and second order mechanisms are not included in the figure.

2.1 The different functions of education

Education shapes individuals' lives in a variety of ways. In particular, formal educational processes based on institutionalized educational programs promote the moral, intellectual, and cognitive development of individuals through instruction in the sense of teaching and training (Smith, 1995). An individual's educational level is assumed to represent skills and knowledge, provides a signal of individual characteristics, and is a symbol of social status (van de Werfhorst, 2011) which provides access to various resources (Kerckhoff, 2001); thus, it can also be expected to affect individual health. The following subchapter provides a brief overview of the central functions of education, which are expected to cause the effects on health.

Several theoretical approaches provide different perspectives on education and the functions relevant for an individual's life (see Figure 2). The first perspective refers to human capital theories and concentrates on the education effects on individuals' skills and knowledge levels (Becker, 1964). From this perspective, it is argued, that with each year in education, individuals acquire additional skills and knowledge, thereby increasing their human capital. The resulting human capital includes general skills and knowledge as it is acquired in formal education educational programs, such as those offered in primary and secondary schools, vocational training or tertiary education. It refers to general skills and knowledge such as reading, mathematical, or problem solving skills, while it also consists of more specific skills and knowledge depending on the vocational orientation of the vocational training or tertiary education (Becker, 1964). Thus, in terms of this approach, an individual's education clearly reflects their general skills and knowledge levels.

Figure 2: Functions of Education



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Secondly, referring to the concept of Bourdieu and Passeron's (1970) definition of institutionalized cultural capital, the signaling theory of Spence (1973), and the screening hypotheses of Arrow (1973), education operates as a signal (or screening device) of the level of incorporated cultural capital, skills and knowledge, and behavior. Under this perspective, education relates closely to the certificates obtained (Bourdieu and Passeron, 1970), and represents a signal for personal characteristics, such as an individual's skills and knowledge levels, personal traits, or motivation. Thus, different levels of education represent different levels of skills and knowledge, attributing different personality traits and behaviors to individuals (Arrow, 1973; Spence, 1974). Consequently, educational credentials, once obtained, have symbolic character and signals someone's productivity levels and other personal characteristics.

Finally, other theories define education as a means of social closure and highlight the symbolic character of education (e.g. Collins, 1971; Parkin, 1974). From this perspective, education represents social power and legitimizes social inclusion or exclusion by expressing the objective legitimization for further education or training, occupational positions, and access to various resources (Parkin, 1974). It refers more strongly to objective credentials obtained, which are assumed to be more important than the actual levels of skills and knowledge acquired in education (e.g. Parkin, 1974; van de Werfhorst, 2011). As a result, based on these theories, education symbolizes social status and marks affiliation to a particular group.

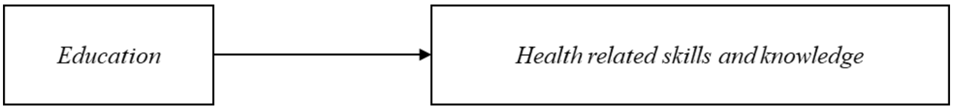
2.2 The effects of education on individuals' (health-related) resources

Since education refers to individual skills and knowledge levels, serves as an additional signal of an individual's characteristics, and defines social status, it is to be expected that education also affects an individual's access to various resources which are important for health. For example, education affects *health-related knowledge and skills*, *occupational status*, *monetary resources*, and *social* and *psychological resources*, all of which are important determinants of individuals' health (Berkman et al., 2000; Grossman, 2006; Link and Phelan, 1995; Ross and Wu, 1995; Ryan and Deci, 2000; Thoits, 2011). The following subchapter briefly summarizes the different pathways linking education to these resources. However, since this covers a very wide range of different theories, I do not claim to provide a complete literature review on all topics, but merely present the most important arguments.

Educational effect on health-related knowledge and skills

The first basic argument for a positive effect of education on health relies on the main principles of the human capital theory and the theory of skill formation based on Becker (1964), Grossman (2006), and Cunha and Heckman (2007). It is assumed that higher skills and knowledge levels acquired in education increase individual *health-related knowledge and skills* (Grossman, 2006) (see Figure 3). Education enhances general cognitive and non-cognitive skills, which foster the ability to acquire new *health-related knowledge and skills*. This is because skills and knowledge acquired in one stage increase levels of self-productivity in future periods (Cunha and Heckman, 2007). Thus, since education increases individuals' abilities to read and calculate, to solve problems, and to master complex tasks and challenges, it is assumed that education also affects their abilities to acquire the knowledge needed to take care of themselves or to function optimally in the health care system (Schillinger et al., 2006). Consequently, the higher an individual's level of education, the higher their *health-related skills and knowledge*.

Figure 3: Effect of Education on Health-Related Knowledge and Skills



Source: Own illustration.

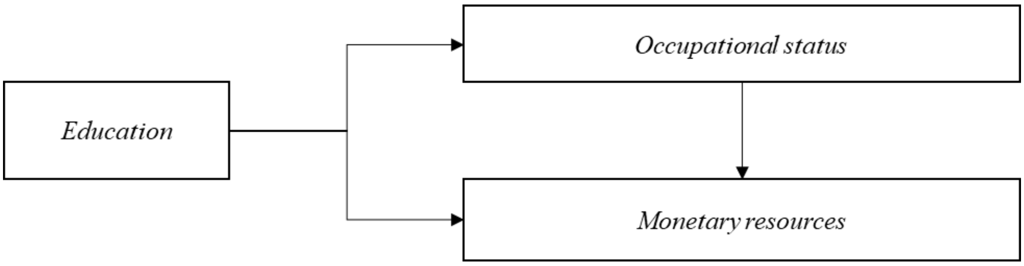
Educational effect on occupational status and monetary resources

A second argument to explain educational differences in health refers to the fact that education increases an individual’s labor market success and correlates with higher o*ccupational status and monetary resources* (see Figure 1 and Figure 4) (Ross and Wu, 1995). This is, firstly, because education affects individuals’ general knowledge and skills, thus increasing their market-related productive and allocative efficiency. Higher productive efficiency means that individuals produce higher levels of outcomes given the same time and investment costs. Thus, individuals who are more productively efficient produce higher outcomes with similar time investments. Allocative efficiency is based on to the assumption that better skills and knowledge increase individuals’ information about the efficiency of an input available for the production of an outcome. As a result, individuals with higher levels of education are more likely to select and combine the inputs with the highest expected outcome. Consequently, they perform better in the labor market because they are more productive while using significantly less time and resources.

Secondly, education is expected to increase individuals’ *occupational status and monetary resources*, because educational credentials serve as signals for individual characteristics, and define someone’s position in the labor queue (Spence, 1974; Thurow, 1976). This is due to the lack of information about individuals’ actual productivity levels in the labor market, which creates uncertainties in hiring processes. Employers need to overcome these uncertainties by relying on alternative strategies, causing them to refer to educational credentials as signals and screening instruments for an individuals’ productivity level and personal characteristics. The higher the level of education, the higher the assumed productivity and the better the expected personal characteristics of an individual. Consequently, employers prefer hiring more educated individuals and are likely to pay them more for their work (Spence, 1974; Thurow, 1976). It can thus be argued that, irrespective of the actual level of skills or someone’s personal characteristics higher education provides access to (higher) occupational positions and better income.

Thirdly, education should affect individual *occupational status and monetary resources* because educational credentials are formal requirements to secure a specific occupational position in the labor market. Educational credentials obtained limit or provide access to specific occupations (e.g. Brown, 1995; van de Werfhorst, 2011). This is because there is an institutionalized demand of formal qualifications which regulates the transition into jobs and organizations (Brown, 1995). Thus, the higher individuals' level of education, the better their chances of finding a job and of reaching a high occupational status.

Figure 4: Education Effects on Occupational Status and Monetary Resources

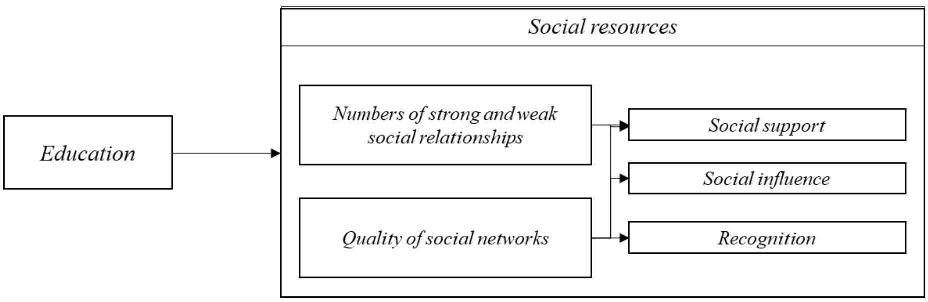


Source: Own illustration.

Educational effect on social resources

Complementing the previously mentioned arguments, a further theoretical strand of literature highlights the relevance of education's effect on individuals' *social resources* within the education-health relationship (Ross and Wu, 1995). Social resources include the degree of social integration in different social ties, the quality of social networks and the degree of emotional, financial and informational support provided by individual networks (Lin, 2002; Thoits, 2011). Thus, in the following, I refer to the effect of education on an individual's number of social relationships, the quality of social networks and the level of social support, as well as the social influence, and recognition available through social networks (see Figure 5).

Figure 5: Effect of Education on Social Resources



Source: Own illustration.

The *number of social relationships* signifies an individual's investments in intimate and informal social networks (strong ties) and their contacts to members of more formal, mostly institutionalized, and larger social groups (weak ties) (Granovetter, 1973). Education affects both the *number of strong and weak social relationships* because depending on the level of an individual's education, they have a different number of meeting opportunities (Erickson, 2004), are more or less socially attractive for others (Erickson, 2004), have different levels of social and verbal skills (Hsung and Lin, 2008), and prefer different investments in the two (Gesthuizen et al., 2008). For instance, more advanced educational levels are associated with more frequent transitions between different educational institutions, increasing individuals' chances of being integrated into the labor market and working in professional positions that involve a higher degree of networking within their workplace (Erickson, 2004). Thus, they have a higher probability of meeting different people. In addition, higher educated individuals are assumed to be more attractive to potential contacts as they represent higher levels of social status and prestige, and have access to more resources assumed to be important for others (Erickson, 2004). Thus, other people should be more willing to stay in contact with individuals with higher levels of education, thereby increasing the numbers of their social relationships and creating advantages in generating social networks within different social circles. Moreover, better social and verbal skills help the higher educated to establish contact and maintain social relationships more easily (Hsung and Lin, 2008). Finally, individuals with higher levels of education tend to invest more in weak ties because weak ties provide the opportunity to perpetuate and reinforce their social status. Lower educated individuals, in contrast, should invest more in strong social ties because they cannot provide the resources needed to invest in weak social ties and, therefore, compensate for this deficiency by investing more in strong social ties (Gesthuizen et al., 2008). As a result, higher levels of education result in a higher *number of strong and weak social relationships*.

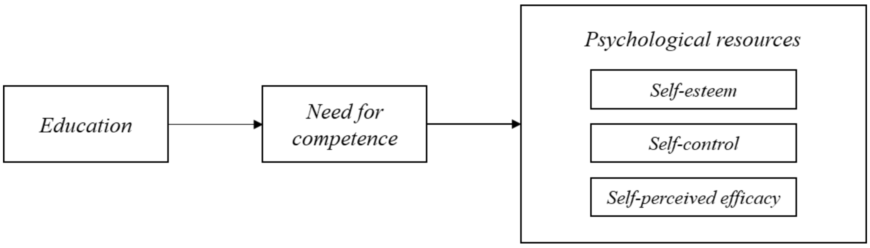
In addition to the effect of education on the number of social relationships, an individual's level of education is also expected to affect the *quality of social networks*, referring to the level of resources available to social relationships. This is because individuals prefer to relate to others who have similar individual characteristics, personal traits, and cultural backgrounds, and have different opportunities to establish contact with resource-rich network partners (Erickson, 2004; McPherson et al., 2001) For instance, with respect to education, individuals are more likely to maintain more relationships with people of a similar education (McPherson et al., 2001). Thus, social networks are separated by educational groups and resource-rich individuals presumably prefer to remain within their own group. Moreover, because individuals are segregated by educational level in school and likewise belong to different institutions later in life, they have different opportunities of coming into contact with resource-rich networks. Thus, the higher educated are more likely to meet resource-rich network partners, because they attend similar educational institutions, and take part in similar organizations and contexts (Erickson, 2004). As a result, higher educated benefit from a higher *quality in social networks*.

The higher *number and quality of social relationships*, in turn, result in higher levels of *social support*, *social influence* and *recognition* available for the higher educated. A greater number of social relationships and contacts to more resource-rich network partners provide higher levels of emotional, instrumental, and informational support and recognition as well as social influence. They also render it more likely that an individual experience feelings of being loved, cared for and secure in uncertain situations, should compensate for a lack of (material) resources to a greater extent, and help with a higher variation of new information (Thoits, 2011). Furthermore, they reinforce a person's sense of identity and increase social influence on important agents (Lin, 2002; Thoits, 2011). Thus, the better an individual's education, the higher their number of social relationships and the *quality of social networks*, and the higher the level of *social support*, *social influence* and *recognition*.

Educational effect on psychological resources

Other resources which are often highlighted in literature as being important for the effect of education on health, relate to inherent psychological processes (see Figure 6) (Ross and Wu, 1995; Ryan and Deci, 2000; Thoits, 2013). For example, Ross and Wu (1995) expect that an individual's levels of *self-esteem*, *self-control* and *self-perceived efficacy* mediate the effect of education on health. Among other factors, education fosters these inherent resources by satisfying the need for competence (Ryan and Deci, 2000). The need for competence refers to an individual's "capacity to interact effectively with their environment - to understand the effects they have on the environment and the effects the environment has on them" (Ryan and Moller, 2007, p. 218). Education can be expected to result in higher levels of need satisfaction, because it raises individuals' levels of skills and knowledge, such as reading and writing skills, analytical skills, and synthesizing (Ryan and Deci, 2000). As a result, better educated individuals are more likely to master challenges and be highly effective in daily life. This, in turn, boosts their levels of self-esteem, self-control, and self-perceived efficacy, because they receive primarily positive feedback to their actions and are able to feel competent in their daily tasks. Therefore, the higher the individuals' education levels, the higher their *psychological resources*, such as *self-esteem*, *self-control*, and *self-perceived efficacy*.

Figure 6: Effect of Education on Psychological Resources



Source: Own Illustration.

To sum up, the theoretical arguments presented thus far highlight that education is likely to raise the levels of different types of resources, available to individuals, which are assumed to explain the effect of education on health (Berkman et al., 2000; Grossman, 2006; Link and Phelan, 1995; Ross and Wu, 1995; Ryan and Deci, 2000; Thoits, 2011). For instance, the higher the level of education, the higher the individual *health-related knowledge and skills*, the probability of achieving a high *occupational status* and generating higher *monetary resources*, of having access to a higher number of social relationships and increased social support, social influence and recognition *(social resources)*, and of having greater of self-esteem, self-control and self-perceived efficacy *(psychological resources)*.

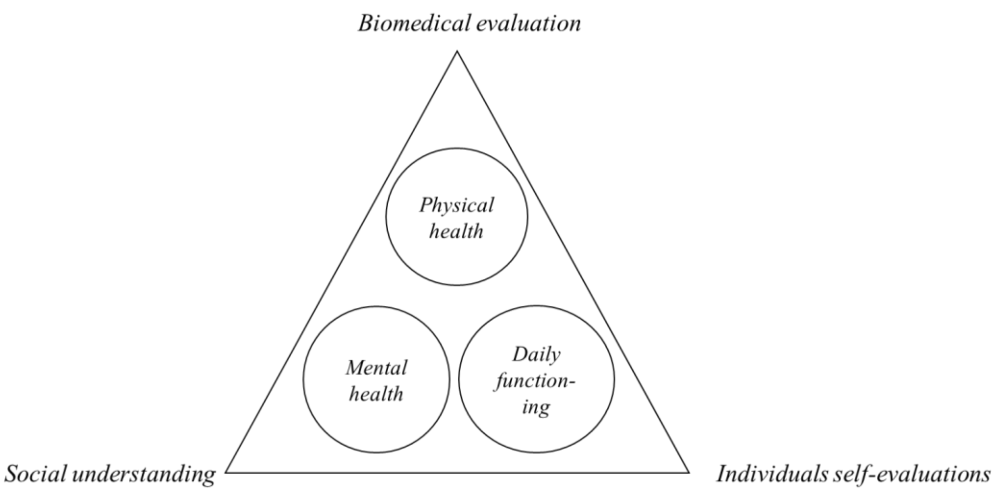
2.3 The effects of education-based (health-related) resources on health

The previous subchapter highlighted the fact that education relates to different types of resources, all of which are expected to influence health. This subchapter is devoted to the question of why these resources serve as important mechanisms in the relationship between education and health. Thus, in the following subsection, I present several arguments linking *occupational status* and *monetary resources*, as well as *social* and *psychological resources* to individuals' health outcomes.

In general, there are multiple perspectives on health in various disciplines, which must be considered in the discussion of the effect of education-based resources on health (see Figure 7 for an overview). They address three different foci: *biomedical evaluation*, *social understanding,* and *individuals' self-evaluations* of health. Concerning the *biomedical evaluation* of health, health can be defined as the absence of illness and disease. Against this background, an individual is defined as unhealthy if infections, genetic defects or organic dysfunctions result in physical or mental symptoms reflecting abnormal body functions and physiological processes, which could be classified in the International Classification of Disease (ICD) (Richter and Hurrelmann, 2009). In contrast, referring to *social understanding*, health is defined as an individual's optimal functioning in daily activities. Thus, an individual would be classified as unhealthy if she or he is impaired in their daily activities or requires any kind of medical treatment (Richter and Hurrelmann, 2009). Finally, considering an *individual's self-evaluation*, the definition of health consists of an individual's own assessment of health, which includes not only the biomedical, but also the social perspective on health. Therefore, an individual would be defined as unhealthy if they defined themselves as such (Erhart et al., 2006; Richter and Hurrelmann, 2009).

With respect to the effect of education on health, however, the subjective evaluation might be of higher importance, since it might well be argued that despite medical diagnoses individuals differ in their subjective evaluations of their overall health status. Depending on their perceived levels of limitations in daily activities, individuals with similar medical diagnoses likely differ in how they define their actual health levels and vice versa. Thus, instead of taking recourse to medical diagnoses and social definitions of illnesses and diseases, it might be of higher relevance to investigate how individuals perceive their own health (Bircher, 2005). In the following, I, therefore, concentrate on explaining why education affects individual's subjective evaluations of health via the different levels of resources.

Figure 7: The Concept of Health



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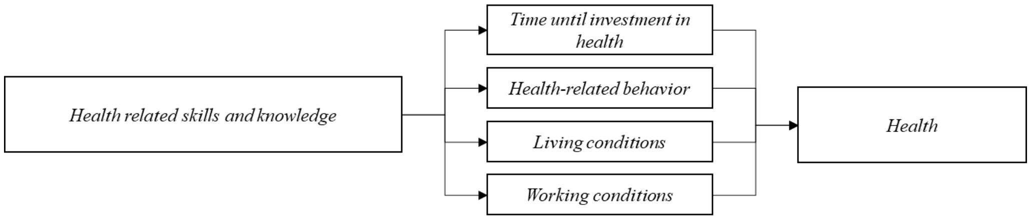
In doing so, I further distinguish between three different dimensions (see Figure 7): *physical health*, *mental health*, and *daily functioning*. *Physical health* refers to the individuals' evaluation of their functional state, as well as their perceived ability of the body to protect the organism from external stressors and to recover from damage or disease (Bircher, 2005; Wilson and Cleary, 1995). In contrast, *mental health* refers to the individual's self-evaluated ability to cope with, manage, and react flexibly to stressful life events and difficult situations, to perform social roles, or to organize and remember information. *Mental health* also includes the individual's perceptions to being able to manage their own emotions, demonstrating empathy, and interacting with others (Galderisi et al., 2015; Huber et al., 2011). Complementing these two dimensions, *daily functioning* addresses the individuals' evaluation of their abilities to meet the everyday challenges of life (Bircher, 2005; Huber et al., 2011; Wilson and Cleary, 1995). However, depending on the resource regarded, there might be differences in the effects on health considering its different impacts on physical and mental health and daily functioning. Therefore, in the following, I describe how the aforementioned education-based resources are expected to affect an individual's subjective evaluation of their physical and mental health and daily functioning.

Effects of health-related knowledge and skills on health

One important determinant of an individual's subjective evaluation of their own physical and mental health, as well as their daily functioning, refers to their levels of *health-related skills and knowledge*. This is because *health- related skills and knowledge* increase an individual's access to information about health-related topics, which not only affects their understanding of health but also helps them to take better care of themselves (see Figure 8). For instance, increased *health-related skills and knowledge* help to make optimal investments during their life cycle by more specifically considering one's existing health status (Grossman, 2006). In addition, the better an individual's *health-related skills and knowledge*, the higher their abilities to detect health problems early on, as they are able to make *timely investments* in medical care and should, consequently, avoid getting seriously or chronically ill (Grossman, 2000; Grossman, 2006). Furthermore, depending on increased *health-related skills and knowledge* levels, people are able to access more information about the harmful and beneficial effects of certain behaviors and life circumstances on health and therefore choose a better mix of resources to invest in their health. For example, they are expected to be more prone to healthy eating, be more likely to participate in preventive checkups when needed, or are more involved in physical activity. Additionally, being more aware of negative health consequences, they are assumed to avoid detrimental *living conditions*, such as bad housing quality, or *working conditions*, and are more likely to avoid risky *health-related behaviors*, such as smoking and high levels of alcohol consumption, to protect their health (Grossman, 2006).

Figure 8: Effects of Health-Related Knowledge and Skills on Health



Source: Own illustration.

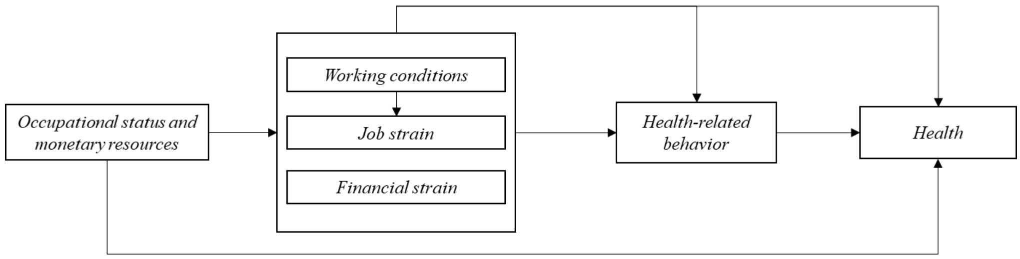
The positive effect of *health-related knowledge and skills*, in turn, should be beneficial to an individual's physical and mental health and daily functioning. This is because the higher an individual's level of *health-related skills and knowledge*, the greater is the probability of considering all three dimensions of health, as individuals can be assumed to be more aware of the different facets of health. Thus, they should invest in their health by considering physical and mental health components and their daily function. As a consequence, they *invest* in health care *in time* to prevent serious and chronic physical and mental illnesses, and invest in *health-related behavior* which not only prevents physical illness but is also beneficial to mental health outcomes and their daily functioning. In addition, they are expected to invest in *living conditions* which contribute to all three dimensions. Therefore, *health-related knowledge and skills* should positively affect individuals' subjective evaluations of their physical and mental health, and daily functioning.

Effects of occupational status and monetary resources on health

Besides the positive effect of health-related knowledge on individuals' health outcomes, higher *occupational status* and higher levels of *monetary resources* are assumed to positively impact health (see Figure 9) (Kawachi et al., 2010; Link and Phelan, 1995; Ross and Wu, 1996). The *occupational status* indicates an individual's position in the labor market, their employment status, and the type of work they are engaged in. It defines, for example, someone's *monetary resources*, working characteristics, their job-related hierarchical position, and prestige (Hodge, 1981). Thus, the factor of *occupational status* is assumed to represent risks and benefits for all three dimensions of health (Hoven and Siegrist, 2013). For instance, an individual's occupational status prevents negative health risks because it strongly affects *monetary resources*. Higher levels of *monetary resources* increase individuals' capacities to meet their daily needs, reduce their *financial strain*, allows for higher investments in positive *health-related behavior* (such as better nutrition, physical activities, and preventive health care) and living conditions (high quality of housing characterized by a less noisy environment, well-lit living spaces, dry indoor climates, or neighborhood green spaces) and thus decreases physical and mental distress (Grossman, 2006; Kawachi et al., 2010; Link and Phelan, 1995; Marmot, 2002; Ross and Wu, 1995). This positively affects physical health because improved *health-related behavior* and living conditions reduce the risk of chronic physical diseases, such as asthma or diabetes (Kawachi et al., 2010). It also affects mental health because lower levels of mental distress reduce the risk of depression or anxiety disorders (Hill and Maimon, 2013; McLeod, 2013). Finally, *monetary resources* decrease limitations in daily life because people invest more in physical fitness, better nutrition, and preventive medical care, all of which reduce the risk of functional limitations.

A higher occupational status also is associated with better health through improved *working conditions* and lower levels of *job strain* (Link and Phelan, 1995; Ross and Wu, 1995). For instance, high-level occupational positions are more often associated with better work-time arrangements, and are less likely to involve high-risk and physically demanding jobs. Thus, individuals in superior occupations have a lower risk of physical and mental distress, work-related health problems, and injuries (Morefield et al., 2012). In addition, higher occupational status reduces individuals' levels of *job strain* because, while highly prestigious jobs in a high-ranking position are often determined by an increased workload, they also allow for high levels of autonomy. This reduces psychological strain and stress, as those affected perceive a high degree of control. Thus, individuals show lower levels of chronic physical and mental distress, which in turn decreases the risk of coronary heart diseases and mental illnesses (Cottini and Lucifora, 2013; Nyberg et al., 2013). In addition, individuals are less likely to compensate the higher levels of distress with negative *health-related behavior*, thereby preventing worse health outcomes. In addition, individuals within these jobs have a lower risk of coronary heart disease and mental health issues due to the lower levels of physical and mental distress perceived (Berkman et al., 2014; Karasek, 1979). Consequently, these mechanisms all lead to the expectation that occupational status affects individuals' physical and mental health evaluations.

Figure 9: The Effects of Occupational Status and Monetary Resources on Health

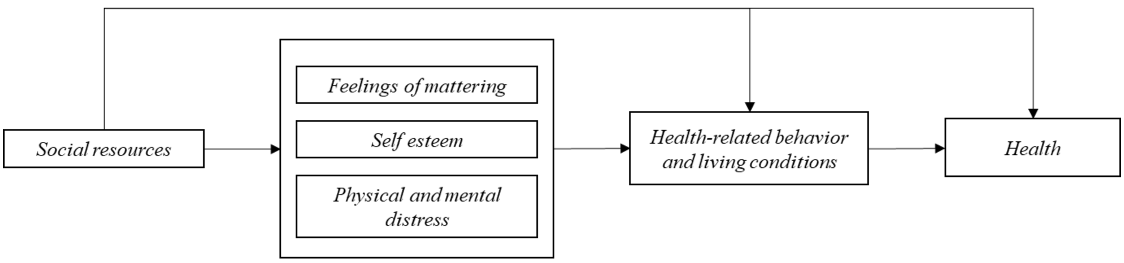


Source: Own illustration.

Effects of social resources on health

Apart from the previously mentioned effects of education-based resources on health, social resources further affect individual health (see Figure 10), as a higher *number of social relationships* correlates with various *role obligations* and higher levels of *social influence*. This positively contributes to health, because, on the one hand, role obligations provide behavioral guidance, feelings of purpose, and meaning in life, being likely to encourage people to avoid risky *health-related behavior* and to take better care of themselves (Berkman et al., 2000; Thoits, 2011). On the other hand, higher levels of social influence affect individual *self-esteem,* which is associated with a lower risk of anxiety, depression, or distress, leading to lower levels of detrimental *health-related behavior* which in turn results in better physical and mental health (Berkman et al., 2000; Thoits, 2011). Thus, a higher number of social relationships can be assumed to positively affect individuals' physical and mental health.

Figure 10: Effects of Social Resources on Health



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Furthermore, social resources are linked to better health because a higher *quality of social contacts* introduces positive adjustments or prevents negative changes in *health-related behavior*. Resource-rich networks partners, who are generally highly educated, are more likely to be regularly physically active, to exhibit healthy dietary behavior, and to avoid smoking, alcohol consumption, and drug intake. Consequently, they act as positive role models, providing positive normative and behavioral guidance, and can thus be expected to positively affect an individual's *health-related behavior* (Berkman et al., 2000; Thoits, 2011). This affects individuals' physical health, as they are less likely to smoke, consume less alcohol and drugs, are more physically active, and show healthier nutrition values that prevent physical health risks such as cancer, liver cirrhosis, cardiovascular diseases, diabetes or asthma (Ross and Wu, 1995). In addition, it also affects mental health, because for instance lower levels of alcohol consumption reduce the risk of major depression, and lower levels of drug abuse decrease the risk of schizophrenia, fatigue, and mood disorders (Lieb, 2015).

Finally, higher levels of actual and perceived social support, such as emotional, informational, or instrumental support, reduce individual *physical and mental distress*, and improve *self-esteem*. For example, higher actual levels of social support reduce the negative consequences of financial hardship, involuntary job loss, or detrimental living conditions by providing alternative resources, such as money, information on vacant positions, or alternative housing as compensation (Thoits, 2011). Thus, social support reduces *physical and mental distress* in these situations. In addition, daily interactions exhibit a positive effect on health since individuals are able to communicate with others about daily strains and challenges, which provides low-barrier emotional support and reduces the negative impact of daily stressors (Berkman et al., 2000; Thoits, 2011). Moreover, perceived social support increases an individual's *self-esteem* by stabilizing self-worth and providing feelings of mastery and perceived control over their life (Thoits, 2011). This reduces negative physical reactions to daily distress and critical life events and prevents negative compensatory strategies in health-related behaviors, such as smoking or alcohol consumption. As a result, social support positively affects an individual's physical health. In addition, it also has impacts on mental health, since it prevents *mental distress* due to daily hassles and uncertain situations, stabilizes individual *self-esteem*, and similarly prevents negative *health-related behavior* (Berkman et al., 2000). Consequently, individuals with higher levels of social support can be expected to have better physical and mental health, and also suffer less from daily limitations.

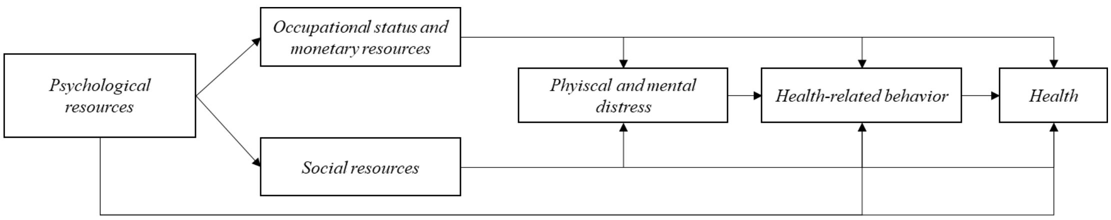
Effects of psychological resources on health

The final group of major resources in education related to individual health consists of inherent psychological factors. The main idea is that education satisfies one of three innate, essential, and universal needs, namely the need for competence, which must be satisfied to generate health and wellbeing.[1] It is argued that individuals cannot remain healthy without satisfying this need

[1] The other basic needs are: the need for autonomy and the need for relatedness (Ryan and Deci, 2000).

(Ryan and Deci, 2000), as satisfying the need for competence increases *self-esteem*, *self-control,* and *self-perceived efficacy*, all of which are expected to affect health (Ross and Wu, 1995) (see Figure 11). For example, a higher degree of *self-esteem* has a positive impact on health because it enables individuals to maintain their autonomy in daily life and to be successful in other life domains (Marmot, 2003): they are, for instance, more likely to overcome the negative impact of peer pressure (Dumont and Provost, 1999), thereby arguably being able to prevent the risk of adapting to negative *health-related behavior* (Torres and Fernández, 1995). In addition, higher self-esteem is assumed to affect other important life outcomes, such as successful integration into the labor market, higher *occupational status,* and *monetary,* or *social resources*, all of which are positively linked to health (Orth et al., 2012). Furthermore, an increased sense of self-control should have a beneficial impact on health by raising individuals' awareness levels and by initiating preventive *health-related behaviors* and positive changes to harmful factors. It helps to avoid detrimental *health-related behaviors*, such as smoking, alcohol abuse, or drug intake. Furthermore, having increased levels of *self-perceived-efficacy* enhances an individual's perceptions of mastering daily challenges and coping with new stressors (Thoits, 2011). This reduces everyday *physical and mental distress* and correlates with lower risks of detrimental *health-related behaviors* and negative physical and mental reactions (Thoits, 2011). Therefore, higher levels of *self-esteem*, *self-control,* and *self-perceived efficacy* can be assumed to affect individuals' physical health, because lower levels of detrimental health-related behaviors decrease the risks of various organic diseases (Berkman et al., 2000; Thoits, 2011). However, it should also affect mental health and daily functioning, since all three factors help to cope with daily challenges and prevent harmful reactions to critical life events (Thoits, 2013).

Figure 11: Effects of Psychological Resources on Health



Source: Own illustration.

To sum up, different theoretical approaches signal a causal effect of education-based resources on health. Based on various theories, *occupational status* as well as *monetary*, *social* and *psychological resources* can be expected to affect individual health. By addressing several mechanisms, these approaches argue that such resources enforce physical and mental health, and should also affect daily limitations. Since they are strongly related to individual education levels, I expect that these resources also explain differences in individuals' subjective evaluations of their physical and mental health status as well as their perceived level of daily functioning by education levels. Therefore, I hypothesize that education is causally related to health through its effects on *(health-related) knowledge and skills*, the *occupational status* and *monetary*, *social* and *psychological resources*.

2.4 Differences in the education-health relationship by individual age

The theoretical arguments presented so far argue in favor of a causal effect of education on health. However, the effect of individual educational levels on health is assumedly more or less pronounced in different stages of the life course. For example, if young individuals are still strongly tied to their family background and have not yet received an education, the effect of education on health is presumably negligible - only if an individual has received some schooling, does education have the potential to influence health. In addition, the effect of education on health needs time to develop, since the highlighted theoretical resources important to improve an individual's health need time to be generated (Lynch, 2003; Ross and Wu, 1996). Thus, the effect of education on health should vary over the life span.

Based on these general assumptions, the effect of individual educational levels on health should be observable for the first time during later childhood and adolescence. Older children and adolescents spend more time in school and thus outside the immediate household, which increases both their autonomy levels and the impact of school on their everyday life. An increased sense of autonomy should contribute to the detachment of adolescent behavior and can be expected to increase self-responsibility (Chen et al., 2002). Thus, one's own knowledge and abilities should become increasingly important, as older children and adolescents start to behave more autonomously and independently of familial background, and their skills and knowledge levels may begin to influence their (health-related) behavior. In addition, school-related experiences and contacts with peers are assumed to shape their social and psychological resources leading to initial differences in health-related behavior, and, thus, health. For example, children begin smoking, drinking alcohol, or trying illicit drugs in the age-range between 11 and 14 (ESPAD Group, 2020; Inchley et al., 2018; World Health Organization, 2019), and the initiation of such detrimental health behavior is strongly associated with children's academic performance and schooling (e.g. Rathmann et al., 2016; Spear and Kulbok, 2001). However, the effect is likely to be weak in the early stages of childhood and then increases with age, as these initial effects of education take time to influence physical and mental health, and daily functioning. All in all, although the effect of education on health should be weak, the effect is likely to be observable in later childhood and adolescence for the first time.

Following the increasing relevance of the effect of education on health during adolescence, the effect of education on health in adulthood takes also some time to develop (Mirowsky and Ross, 2005). For instance, although education is assumed to benefit individual skills of investing in a healthy lifestyle, positive health effects are usually observed later on. This is because the allocation of individual stock of occupational, monetary, social, and psychological resources, is a time-dependent process. After school, additional investments are needed to generate income, to find a good job, to reach a higher level of living standards, or to benefit from resource-rich social networks (Lynch, 2003; Lynch, 2006; Ross and Wu, 1996). Therefore, the expected effects on health require time to become manifest, as the aforementioned factors must first develop and take effect.

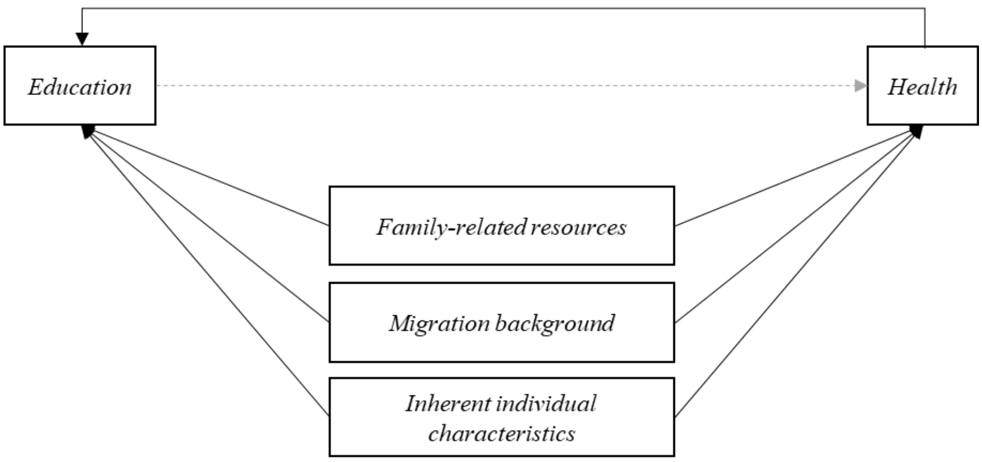
Thus, the impact of education on health should be stronger at higher ages and later stages of the life course since individuals are by this time able to allocate additional resources based on their labor market position and their social networks. Depending on their educational level, individuals reach different levels of income and wealth given their occupational status, are exposed to better or worse working conditions, and generate social and psychological resources that contribute to their health. The higher the level of resources allocated, the higher the expected benefits on health. Therefore, in later adulthood, individuals with better education should enjoy more benefits to their health due to a higher levels of resources. They are more easily able to make the investments necessary to stay healthy or to fully recover from an illness. In contrast, individuals with low levels of education are expected to suffer from less effective resource allocation and, thus, should have a lower health status (Ross and Wu, 1995). Therefore, the effect of education on health is assumed to be pronounced more strongly in later adulthood.

To sum up, the causality of the link between education and health significantly depends on the life stage considered. While in early childhood education is not able to affect individuals' health, the effect of education on health can be expected to be initially observable in later childhood and adolescence. In addition, the effect of education on health should be best observable in (later) adulthood. Therefore, examining the causal effect of education on health should always take into account the different circumstances within the individual age groups.

3 Selection processes affecting the education-health relationship

Aside from theories suggesting a causal effect of education on health, there exists another strand of literature which discusses the relevance of selection processes in the education-health relationship. Selection processes, on the one hand, refer to reversed causality and thus signify the effect of individual health on education. On the other hand, they rely on confounding factors related to important background characteristics that affect both education and health outcomes. Thus, theoretically, not only is education assumed to affect individual health, but health is also expected to be an important prerequisite for acquiring education. In addition, important background characteristics may confound both relationships (for review see for example Hoffmann et al., 2019; Lynch and Hippel, 2016) (for an overview see Figure 12).

Figure 12: Reversed Causality and Confounding Factors



Source: Own illustration.

3.1 Reversed causality: The effect of health on education

One argument countering education's causal effect on health relates to the notion that health is a prerequisite for education and that healthier individuals are selected at higher levels of education. This is, firstly, because health exposures affect children's cognitive growth and development. Critical exposures at certain periods have harmful long-term effects on body structure and organ function (biological programming) and, thus, affect children's brain development (Ben-Shlomo and Kuh, 2002). For example, early infectious diseases divert necessary nutrients away from the brain and hamper neurological development, since the biological system has to mobilize immune functions as defense against the infection (e.g. Bhalotra and Venkataramani, 2013). This is likely to result in lower levels of educational achievement, as children with impaired cognitive development are less able to acquire skills and knowledge in comparison to children with higher levels of cognitive growth (Lynch and

Hippel, 2016). Secondly, it is also possible that illnesses affect individuals' education because of the decreased time of school attendance, as lower levels of health result in higher levels of school absence due to illness. Children miss time in school and fall behind the academic performance levels of their peers. As a result, children with high shares of days absent from school are at higher risk of grade repetition and show lower levels in grade point averages and lower performance levels. This is assumed to lead to a lower level of education because children with poorer school grades and performance levels are at higher risk of being assigned to less prospective school tracks and have less chances at upward mobility in the educational system (Jackson, 2009). Finally, it might be possible that individuals diagnosed with life-threatening illnesses invest less in their educational attainment because of a limited sense of future orientation. Individuals with poor health should thus expect lower return levels to education and higher opportunity costs because of their decreased subjective life expectancy (Lynch and Hippel, 2016). In short, despite of the effect of education on health, illness and disease also affect individuals' educational outcomes, because of biological, educational, and decision-making processes that select individuals into lower levels of education.

3.2 Indirect selection or the relevance of important background characteristics

Besides the theoretical arguments accounting for reverse causality, the effect of education on health also could be undermined by a spurious correlation between the two. Important background characteristics might affect both individual health and education, and may serve as back-door paths in the relationship. Theoretically, it is easily arguable, that, firstly, *family-related resources* such as parental education or income affect both children's health and their educational performance. Higher levels of parental education are associated with higher levels of skills and knowledge and, thus, lead to better and more efficient investments in children's health and education. For example, parents with better education more efficiently invest in preventive measures during pregnancy, for example, (early) medical health care for themselves and the child. They are also assumed to invest more strongly in other positive health-related behavior related to their own and their children's health. Moreover, parents with a higher education level spend more time on the advancement of their children's cognitive growth and learning processes (Boudon, 1974; Grossman, 2006). Finally, parents with higher educational levels have more resources available to foster their children's health and education results. They also have higher degrees of labor market-related and social resources available, which, for instance, allow for better investments in the standard of living, better nutrition or medical health care, and in additional support for education, such as private tutoring, additional courses or learning material. This can be expected to positively affect children's health, cognitive growth, and educational performance (for a review see Case and Paxson, 2010).

Other theoretical arguments suggest that individuals' *migration background* may also act as a confounder in the relationship between education and health. For instance, individuals with migration backgrounds show lower levels of specific information about the educational setting in the host country, which hinders their ability to successfully make transitions within the education system and to make beneficial educational choices. In addition, discrimination processes in educational contexts are assumed to hamper the educational success and competence development of individuals with migration backgrounds. Furthermore, low levels of language skills complicate the acquisition of skills and knowledge in education (for review see Kristen and Granato, 2007). In addition, migration background is assumed to have positive effects on health because only those who are in good physical and mental condition can migrate successfully (Razum, 2006). Furthermore, it indicates differences in health, as cultural habits affect individual health behavior such as dietary behavior, substance use, and alcohol consumption, both positively and negatively (Kleiser et al., 2010). Moreover, individuals with a migrant background might differ in their health compared to native residents, as cultural differences between the country of origin and the host country may lead to culture shocks and promote daily stress factors, especially among first-generation migrants (Shishehgar et al., 2015). Moreover, individuals with migration backgrounds can be expected to be in poorer health because lower language skills limit their access to health care and medical interventions and result in increased levels of daily distress, resulting in mental health constraints and stress-related physical health impairments (for review see Shishehgar et al., 2015). Therefore, an individual's migration background significantly affects education and health outcomes and, thus, confounds the relationship between education and health.

In addition to family- and migration-related differences in individual education and health, some *inherent individual characteristics* are also thought to be confounding elements. For example, genetic factors arguably explain differences in education and health resulting in a spurious correlation between the two. A various number of diseases and chronical illnesses are known to be determined by genetic factors, such as diabetes, cystic fibrosis or the Huntington disease. In addition, the interaction of genes with environmental factors result in diseases and illnesses based on changes in, for example, the enzyme system or polymorphic traits (Khoury, 1996). Genes are furthermore argued to affect individual cognitive abilities (intelligence) and learning abilities, because they contribute to brain functions and development (Plomin, 1999). Furthermore, individual personality traits might affect both, an individual's education results and their health status.[2] On the one hand, personality traits affect an individual's level of education, because they are linked to learning and educational success (e.g. Lenton, 2014). On the other hand, personality traits also influence individual health, because they initiate emotional states that affect physical health reactions by influencing a person's levels of daily distress and leading to different health-related lifestyles and utilization of health care services (Contrada et al., 1990). In addition, individuals' preferences should result in systematic differences in education and health. For example, time preferences are important for education and health because individuals have to choose between current and future outcomes of the two (van der Pol, 2011). They are important for education because education decisions can be risky and individuals do not know the exact returns and costs of higher education, thus making investments based on individual risk preferences. Complementing this, individuals' risk preferences should also determine their health, as they are closely related to consumptive and behavioral choices, which should affect their health-related behavior and investments in health (Anderson and Mellor, 2008; Friedman, 1974). Therefore, among other factors, these individual-specific characteristics might cause a spurious correlation between education and health.

To conclude, different selection processes are expected to undermine the causal effect of education on health. Despite education's causal effect on health, the causal impact of health on education and confounding factors could be relevant in the link between the two concepts. Therefore, the study of the causal effect of education on health must take into account the different arguments of selection processes.

4 State of research and contribution

Studies of the relationship between education and health have a long tradition and focus on different aspects of this relationship (Grossman and Kaestner, 1997). In particular, an increasing number of studies examines whether education causally affects the overall health status of individuals, the prevalence of mental and physical illness, and various health-related behaviors which are strong predictors of individual health status (for review see Galama et al., 2018; Hamad et al., 2018; Xue et al., 2021). Another group of studies investigates to what extent theoretical mechanisms contribute to the relationship between education and health (for a review see Lleras-Muney, 2005; Xue et al., 2021). Finally, some studies indicate effect

[2] They are also good arguments that education shapes personal traits, which might also affect individuals' health (Anger and Dahmann (2014)). However, given the theoretical framework developed in the previous subchapter, I only consider personal traits as confounding factors in the education-health-relationship.

heterogeneity by age since they focus on specific age groups (e.g. Braga and Bratti, 2013; Gatz et al., 2007; Seglem et al., 2020). As a result, the body of literature on the various topics has grown considerably in recent decades.

Therefore, I review the main results of these three topics related to the effect of education and health in this section. In analogy to the structure of the theoretical background, I firstly summarize the literature by discussing the relationships between different dimensions of education and all three dimensions of health. Secondly, I summarize the literature focusing on mechanisms linking education to health, and, thirdly, present empirical evidence regarding differences by individual age. Finally, I discuss the importance of reversed causality and confounding bias highlighted in different types of causal studies. I outline the main findings and refer to meta-analyses and reviews if available. In closing, I summarize the main limitations and research gaps, and develop the contribution of the thesis to the existing literature.

4.1 Evidence for different measurements of education and health

Since there is a wide range of studies published in the last decades which analyze the relationship between education and health, there is also a high variation in empirical evidence (Galama et al., 2018; Hamad et al., 2018; Xue et al., 2021). This is, on the one hand, because studies address different dimensions of education and health. For example, they focus on years of schooling or education certificates, or distinguish between different groups of education (low, middle, high) to investigate the relationship between these measurements and health. In doing so, they focus either on medical diagnoses or individuals' self-assessments of their physical health, mental health, or daily functioning. Therefore, this subsection summarizes the existing evidence for different measurements of education and health.

A considerable amount of studies examines health differences by individuals' *years of education* (Hamad et al., 2018; Xue et al., 2021). In general, this serves as an indicator for an individual's time spent on education and, in line with a human capital perspective, primarily represents someone's investments in general skills and knowledge. The main argument is that with each *year of education,* individuals gain new skills and knowledge. Years of education are based either on an individual's self-reported time spent in school or are constructed from their highest educational certificate obtained. Thus, depending on the measurement of *years of education*, different levels also represent education certificates since the *years of education* necessary to obtain a certain certificate are mostly standardized (Schneider, 2015). For the impact of education on health, measurements of *years of education* often suggest empirical relevance of education on several health outcomes reflecting individuals' physical and mental health and daily functioning (Hamad et al., 2018; Xue et al., 2021).

A further body of literature addresses the relevance of *educational certificates*. Such studies mostly use a categorical operationalization of education on health, reflecting the highest *educational certificate* obtained in life. They additionally cover the signaling and the status dimension of education, as certificates not only represent the years spent on education by an individual, but also his or her educational achievements (Schneider, 2015). Thus, they additionally investigate how education – as a signal of skills and knowledge, and as a symbol of social status - affects individual health. These studies demonstrate only a small impact on individuals' health outcomes, such as subjective evaluations of overall health status, sickness absence, body mass index, or physical functioning (Amin et al., 2015; Benson et al., 2018; Furnée et al., 2008; Ross and Mirowsky, 1999; Seglem et al., 2020). In addition, a recently published meta-analysis by Xue et al. (2021) suggests that studies using *educational certificates* tend to report, on average, a smaller impact of education on all three health dimensions in comparison to studies focusing on *years of education*, although the difference is not statistically significant.

Regarding the variation by the educational dimension addressed, only two studies directly examine the differential relevance of the two educational dimensions most commonly used in literature, *years of education* and *educational certificates*, in their effect on health. A first study provided by Ross and Mirowsky (1999) support the findings of the meta-analysis. By using a U.S. sample of adults aged between 18 and 95, they highlight, that beyond the positive link of *years of education* on individuals' self-reported overall health and daily functioning, *educational credentials* do not contribute to the relationship. In contrast, the second study by Lundborg (2012) contradicts these findings by using a sample of U.S. twins. Lundborg shows that, compared to *years of education*, the highest *educational certificate* obtained in life seems to be of more relevance for self-reported health status and the risk of having a chronic health condition. In addition, he highlights that neither *years of education* nor the highest *educational certificate* obtained seem to be related to an individual's BMI. Thus, depending on the dimension of education considered, there appear to be differences in the relationship between education and health.

The differences in the relationship between education and health do not only relate to the different operationalizations of education. Depending on the focus of health evaluation addressed, studies reach different conclusions about the impact of education on health. For example, a large number of studies investigates educational differences in individual *self-rated health* as a subjective evaluation of their overall health status (Furnée et al., 2008; Hamad et al., 2018; Xue et al., 2021). Studies using this type of measurement refer to questions such as *'How would you describe your general state of health?'* which ask for a rating of 'very good' to 'very poor'. Individuals' *self-rated health* is one of the most important indicator for understanding and investigating health inequalities (Bruin et al., 1996). It is strongly linked to individuals' actual physical health status and daily functioning, and represents mental health aspects and chronic diseases (Chandola and Jenkinson, 2000; Krause and Jay, 1994; Lundberg and Manderbacka, 1996). It also serves as a good predictor for individuals' mortality risk (Bailis et al., 2003). Studies using this type of measurement of an individual's overall health status generally demonstrate that education is strongly associated with better *self-rated health* (for review see Furnée et al., 2008; Hamad et al., 2018). Consequently, studies highlight the importance of education for individuals' *self-rated health* status.

Another variety of studies, however, refers more strongly to medical diagnoses of physical health and exhibits diverging results (for a systematic review see Hamad et al., 2018; Xue et al., 2021). For instance, studies that investigate educational differences in the risk of *having diabetes* report zero effects of education. Similarly, studies that examine educational differences in the risk of having lung diseases such as *asthma* also show no effect of education on these types of diseases, and studies focusing on educational differences in heart diseases, such as *high blood pressure,* likewise question the impact of education. In contrast, studies focusing on the link between education and *hypertension* or the risk of *having cancer* suggest negative, positive, and zero effects of education on these indicators (Hamad et al., 2018). Thus, compared to the individuals' subjective rating of their overall health status, educational differences in medical diagnoses of physical health are highly disputed (Xue et al., 2021).

Another measurement of individuals' health often used in empirical studies is the *Body Mass Index (BMI)*. The *BMI* reflects an individual's physical constitution and nutrition values and also serves as a proxy for the risk of having cardiovascular diseases (Pate et al., 2012). Studies investigating educational differences in individual *BMI* mostly include the metric value and additionally classify people as being obese or overweight (e.g. Fletcher, 2015; Jürges et al., 2011; Kemptner et al., 2011; Kim, 2016; Reinhold and Jürges, 2010; Webbink et al., 2010). However, while some of these studies show that education reduces individual *BMI* and is thus linked to a lower risk of being obese or overweight (Hamad et al., 2018; Kemptner et al., 2011; Kim, 2016; Reinhold and Jürges, 2010; Webbink et al., 2010), other studies indicate that there are no educational differences in individuals *BMI* or the prevalence of being obese or overweight (e.g. Hamad et al., 2018; Jürges et al., 2011). As a result, it is unclear whether education is linked to individual physical constitution or not.

A further dimension of health often used in empirical studies includes individuals' daily limitations and functional abilities. Studies addressing this dimension often refer to individuals' *work disabilities* (e.g. Kemptner et al., 2011), *physical limitations* (e.g. Courtin et al., 2019), such as low walking speed and low levels of grip strength, or general indicators for *daily health-related limitations* (e.g. Braakmann, 2011; Mazumder, 2008). Empirical results suggest either zero or beneficial effects of education. While, for example, Kemptner et al. (2011) show preventive effects of education on work disabilities for men and Mazumder (2008) shows weak effects of education on speaking problems and trouble with hearing, Courtin et al. (2019) and Braakmann (2011) finds no effects of education on these types of health indicators. As a result, Hamad et al. (2019) summarize that results for daily limitations are inconclusive, with half of the studies suggesting an effect of education on this dimension of health and the other half of the studies not observing this effect.

Despite these aforementioned health indicators, some further studies address individuals' subjective evaluations of their mental health. This part of the literature primarily addresses educational differences in indicators that focus on *depressive symptoms* and *anxiety* (Avendano et al., 2020; Chevalier and Feinstein, 2006; Crespo et al., 2014; Viinikainen et al., 2018). They use specific scales developed to assess individuals' level of depression or anxiety (Avendano et al., 2020; Crespo et al., 2014; Viinikainen et al., 2018), such as the CIS-R or the EURO-D scale, or the mental health score of the short-form health questionnaire (SF-12) (Dahmann and Schnitzlein, 2019). Some others use scales measuring *cognition status* to investigate educational differences in memory diseases (Crespo et al., 2014; Glymour and Manly, 2018; Schneeweis et al., 2014). However, most of these studies do not show educational differences in mental health outcomes (Hamad et al., 2018; Xue et al., 2021). Only a very small number suggests that education affects individuals' level of depressive symptoms and anxiety (Avendano et al., 2020; Chevalier and Feinstein, 2006; Crespo et al., 2014). It, therefore, remains unclear whether education affects individuals' mental health outcomes.

In sum, studies investigating the effect of education on health exhibit a high variation of measurements used. First, they differ in their operationalizations of education, either concentrating on the years of education or the highest level of education obtained in life. Second, studies concentrate on a different dimension of health using either subjective evaluations or medical diagnoses. As a result, empirical evidence strongly diverges in its conclusions about the effect of education on health.

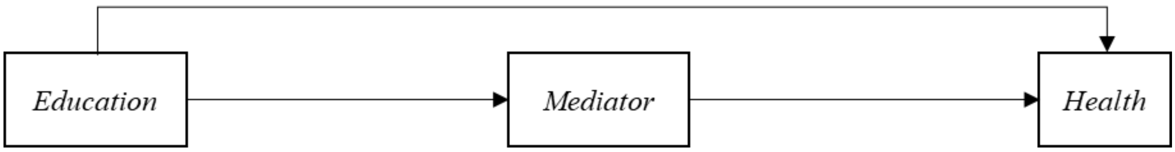
4.2 Evidence about mechanisms relevant for the effect of education on health

A further branch of literature focuses on the mechanisms in the education-health relationship to test the relevance of theoretical arguments. For the systematic review, I focus on the literature on mediating effects of education-related resources, which I previously identified as particularly relevant. I refer specifically to *health-related skills and knowledge*, *occupational status* and *monetary resources*, *social*, and *psychological resources*. However, I only exemplarily describe some of the studies investigating the mediations, detailed information on all studies are available in Table A1 in the Appendix.

In general, mediation analyses claim to explain why a specific treatment affects an outcome and aim to identify the processes which lead to this effect (VanderWeele, 2015). A mediation occurs if a treatment or explanatory variable (X), here education, affects an outcome variable (Y), here health, and another variable, the mediator (M), explains a part of the effect of X on Y (see Figure 13). Thus, to identify mediation in empirical analyses, studies have to follow four initial steps. First, they have to estimate the relationship between the treatment and the outcome variable (total effect). Second, they must estimate the relationship between the treatment and the mediator and, thirdly, predict the indirect effect of the treatment on the outcome due to the mediator (Baron and Kenny, 1986). Finally, they should test, whether the difference between the total effect and the indirect effect are statistically significantly different from zero. In doing so, however, they are only able to identify a real mediation if they could eliminate any confounding variables affecting the treatment, the outcome, and the mediator under investigation (VanderWeele, 2015).

In empirical literature, however, there is a high variation of methods used to investigate mediation effects (for an overview see Mustillo et al., 2018; VanderWeele, 2015). For instance, following the approach of Baron and Kenny (1986), some studies use the product-method to identify the mediation effect. The product-method provides consistent mediation effects estimated from the product of the coefficients predicted in linear regressions with continuous outcomes. This refers to the predicted estimate of the effect of the treatment on the outcome variable and the predicted estimate of the mediator on the outcome conditioned on the treatment. Others, however, use the procedures suggested by Breen et al. (2013) (KHB method), Tingley et al. (2014), or VanderWeele (2015), which more strongly emphasize the causal interpretation of the estimates and highlight the importance of confounding variables and the moderated mediation effects (causal mediation analyses). They suggest the difference-approach to estimate the meditation effect of a treatment on an outcome via the mediator. The difference-approach provides a consistent estimate by the difference of the total effect of the treatment on the outcome and the effect of the treatment on the outcome conditioned on the mediator if the underlying regression models are unbiased regarding confounding. For testing the significance of the mediation, most studies employ tests proposed by, for example, Sobel (1996), MacKinnon et al. (2002), or McDonald and Moffitt (1980).

Figure 13: Mediation between the Treatment Variable Education and the Outcome Health



Source: Own illustration.

(Health-related) skills and knowledge

The first part of the literature assesses the relevance of *(health-related) skills and knowledge* in the link between education and health. These studies mostly address the theoretical arguments of the human capital theory and focus either on health literacy or health-related knowledge levels to examine whether these explain some part of the positive association between education and health. Studies focusing on health literacy investigate whether "people's knowledge, motivation, and competences to access, understand, appraise and apply health information in order to make judgments and take decisions in everyday life concerning healthcare, disease prevention and health promotion" (Sørensen et al., 2012, p. 3) explains some part of the association between education and health (Lastrucci et al., 2019; Schillinger et al., 2006; van der Heide et al., 2013). In contrast, empirical research on the mediation of health-related knowledge focuses more strongly on individuals' knowledge about general and specific health-related topics (e.g. Hoffmann and Lutz, 2019; Kenkel, 1991; Mocan and Altindag, 2014).

Empirical results suggest, that health literacy partially explains the relationship between education and health (Friis et al., 2016; Lastrucci et al., 2019; Schillinger et al., 2006; van der Heide et al., 2013). For instance, Lastrucci et al. (2019) show that the educational level, operationalized in terms of holding a bachelor's or master's degree, indirectly affects an individual's self-rated health status through different levels of health literacy. They do this using a non-representative sample of the population in Florence, Italy, aged 18-69 years, and employ causal mediation analyses as proposed by Tingley et al. (2014). Similarly, van der Heide et al.

(2013), testing the mediation with the product-of-coefficients test proposed by MacKinnon et al. (2002) based on different regression models, establish that health literacy mediates the positive effect of the level of education on reporting good general health in a representative Dutch sample of adults aged between 25 and 65. They provide evidence for indirect effects of primary, lower secondary, upper secondary, and tertiary education. In addition, Schillinger et al. (2006), Bennett et al. (2009), and Friis et al. (2016) support that health literacy explains some part of the differences in individuals' health and health-related behaviors. Thus, these studies reveal a mediation of individuals' health literacy levels in the effect of education on health.

In terms of health-related knowledge, no study has yet examined mediation in the relationship between education and health and there are only a few studies that test the mediation effect for the relationship between education and health-related behavior. Therefore, I now exemplify the results on health-related behavior because they are important determinants of health. To the best of my knowledge, except for one study provided by Hoffmann and Lutz (2019), results support only small or negligible mediation. For example, Kenkel (1991) and Mocan and Altindag (2014) indicate that there seems to be only a very weak mediation effect of time spent in schooling on individuals health-related behavior, such as alcohol consumption levels, smoking, and physical activity, through health-related knowledge levels in representative U.S. samples containing adults and adolescents, respectively. In contrast, using data of adults aged under the age of 44 living in the Philippines, Hoffmann and Lutz (2019) show that knowledge explains about 65 to 69% of the effect of years of education on health-related behavior and lifestyle (for example, physical activity levels, dietary behavior, medical health care, hand washing, and not drinking untreated water) by using the KHB method. Taken together, thus far, although empirical results suggest a mediation effect of individuals' health literacy, they do not provide similarly unambiguous evidence for health-related knowledge.

Occupational status and monetary resources

Beside the studies investigating the mediation of health-related skills and knowledge in the education-health relationship, another large number of studies examine how labor-market related aspects contribute to the link. Such studies concentrate on the mediation effects of labor market returns of education such as individual income, occupational status, and working conditions (for overview see Cutler and Lleras-Muney, 2006). In addition, some studies aim to identify the relative importance of different labor market-related mechanisms in the education-health relationship by testing multiple mechanisms against each other (e.g. Brand et al., 2007; Katikireddi et al., 2016; Lee, 2011; Milner et al., 2018).

Regarding the mediation effect of individuals' occupational status, numerous studies suggest that individuals' occupational characteristics partly explain the effect of education on health. For instance, by employing causal mediation analyses and estimating total, natural direct and indirect effects based on structural equation models in an Australian sample of young adults aged between 20 and 35, Milner et al. (2018) show that individuals occupational status explains more than 30% of the positive association of having completed high school on an individual's overall mental health status. In the same vein, Sheikh et al. (2017) highlight that occupational status largely contributes to the association between the highest educational certificate obtained in life and a person's subjective rating of their overall health status. Furthermore, studies reveal that working conditions and job characteristics, such as authority, physically demanding work, concentration and attention levels, job satisfaction, psychosocial work environment, demand-control, working hours, work-life conflict, and biomechanical strains, additionally mediate the positive effect of years of education. In addition, they show that these factors explain some negative consequences of lower education for several health outcomes such as subjective evaluations of overall health, medical diagnoses, depressive symptoms or functional limitations (e.g. Brand et al., 2007; Hagen et al., 2006; Hämmig et al., 2014; Hoven and Siegrist, 2013; Karmakar and Breslin, 2008; Lee, 2011; Marmot et al., 1998; Qiu et al., 2012; Smith et al., 2013).

Studies investigating the mediation effect of monetary resources in the relationship between education and health also show clear effects on several health outcomes. For example, Brand et al. (2007), using a sample of adult siblings living in Wisconsin (U.S.) and following the approach of causal mediation analyses by employing stepwise family-fixed-effects structural equation models, show that individual job characteristics and income explain about 50% of the effect of years of education on overall health status, musculoskeletal health limitations, and depression. Similarly, using a sample of South Korean adults, Lee (2011) also supports the mediation of income in the association between the highest educational certificate obtained in life and depression, while Milner et al. (2018) and Murrell et al. (2004) do so for general mental health status and fatigue, respectively, indicating strong indirect effects of years of education and completing high school on health via income and economic resources in a causal mediation analysis and an analysis following the suggestions of Baron and Kenny (1986). Likewise, further studies such as those of Ettner and Grzywacz (2003), Lynch (2006), and Sheikh et al.

(2017), indicate that material resources, operationalized as financial strain and income, partly explain the association between the highest educational certificate obtained in life or years of schooling and self-rated health status. Thus, in line with theoretical arguments occupational status and monetary resources both seem to contribute to the effect of education on health.

Social resources

Regarding the mediation effect of social resources, the empirical evidence is strongly limited, as there are only a few studies investigating the indirect effect of education on health through individuals' social resources (e.g. Antonucci et al., 2003; Ettner and Grzywacz, 2003; Lee, 2011; Marmot et al., 1998; Vonneilich et al., 2012). However, taking into account the existing studies, most empirical research suggest that social resources only contribute a small part to the relationship between education and health, all pointing to negligible mediation effects except for one study. While Lee (2011) suggests that for South Korean adults, being married, the number of children, siblings and friends, the integration into the labor market, and social activities explain a significant part of the effect of the highest educational certificate obtained in life on health, four other studies do not support such a strong mediation. For example, analyzing a sample of adults living in an urban area in Germany, Vonneilich et al. (2012) finds only a very small reduction in the predicted estimates of years of education on reporting poor health when an individual's level of social integration, reflected in their marital status, number of close friends, and participation in voluntary associations, is included in the model. Likewise, Marmot et al. (1998), Ettner and Grzywacz (2003), and Antonucci et al. (2003) highlight that these indicators for an individual's number of social relationships do not contribute to the effect of the highest educational certificate obtained in life and reporting poor health, the risk of being overweight, waist-hip ratio or having depressive symptoms, and individuals' psychological wellbeing in the U.S. Therefore, based on the small number of studies, social resources seem to be less pronounced in the relationship between education and health.

Psychological resources

Complementing the aforementioned empirical investigations, some studies contribute to the overall picture by examining the relevance of psychological resources for the effect of education on health. Among other things, these studies investigate how individuals' self-esteem, perceived mastery and control, or helplessness contribute to the education's effect on health. For example, using samples which contain adults living in the U.S. aged between 25 and 74 and between 18 and 95, respectively, Marmot et al. (1998) and Mirowsky and Ross (1998) examine the reduction of education's effect on health by a model comparison and the mediation in a structural equation model, respectively, while considering individuals' perceived mastery and control. Both studies highlight the fact that these psychological resources seem to explain some aspects of the positive effects of educational credentials and years of schooling on reporting poor/ fair physical health, waist-hip ration, psychological wellbeing and a healthy life style. However, since they do not investigate the mediation as suggested by Baron and Kenny (1986) or VanderWeele (2015), it remains unclear whether psychological resources really explain a part of the effect of education on health.

Research gaps and limitations

Although the existing literature provides highly valuable insights, it also lacks answers to important questions addressing the theoretically expected mechanisms. For instance, studies investigating the relevance of health-related knowledge only examine the mediation effects of education on health-related behavior and two of the three studies investigate the mediation for a specific subgroup (Hoffmann and Lutz, 2019; Mocan and Altindag, 2014), which raises questions about the mediation in adults within modern societies. Thus, empirical evidence for individual health is still missing. In addition, although much has been done in the last decades to demonstrate the mediation of individuals' occupational status and monetary resources, there are some research gaps and limitations restricting empirical evidence. A high number of valuable studies demonstrate that income, occupational status, job characteristics, and working conditions mediate some part of the effect of education on health. However, thus far, empirical research on the relevance of income primarily focuses on liberal welfare states (e.g. the U.S. or Australia), only two studies examining the link in other countries (Lee, 2011; Sheikh et al., 2017). It is therefore unclear whether the same results would be obtained in other welfare state systems that partially compensate for an individual's lack of income.

Furthermore, although there are some studies investigating the mediation effect of social resources, there is a lack of research about the relevance of different facets of social resources for the three dimensions of health. For instance, all studies investigate the mediation effect by using combined indices of social resources which include different factors associated. Thus it is unclear which types of social resources really contribute to the effect. In addition, limitations inherent in the studies presented by Lee (2011) and Ettner and Grzywacz (2003) raise questions about the mediation effect in the relationship between education and mental health. While Lee (2011) may overestimate the indirect effect of education on depression via social resources, since Lee also includes labor market participation in her analyses, Ettner and Grzywacz (2003) may arrive at a false conclusion about the mediation effect because of methodological limitations in logistic regression analyses (for a detailed discussion see Chapter 4). Moreover, although there are some studies investigating the mediation effect of some part of the psychological resources, the empirical evidence thus far does not directly test for the mediation. In addition, the studies only concentrate on the mediation of education on health via perceived mastery and control (Marmot et al., 1998; Mirowsky and Ross, 1998) and, thus, research on the mediation effect of education on health through individuals' self-esteem and self-perceived efficacy remains lacking. Furthermore, since both investigate the mediation effect of education on self-rated overall health status, there is no empirical evidence on investigations focusing directly on individuals' physical and mental health or daily functioning.

Along with these open questions regarding the empirical relevance of the aforementioned mechanisms, some limitations further restrict the empirical evidence. On the one hand, incomplete testing of mediation raises questions about the validity of the examined relationships. Some of the research does not clearly identify the mediation as suggested by, for example, Baron and Kenny (1986) and VanderWeele (2015), and a few studies only interpreted changes in coefficients for investigating mediation effects (Ettner and Grzywacz, 2003; Kenkel, 1991; Marmot et al., 1998; Murrell et al., 2004; Vonneilich et al., 2012). In addition, some did not claim the size of the mediation effect and do not test the mediation for statistical significance. Thus, the interpretation of the mediation effects highlighted in these studies is disputable. On the other hand, most studies may suffer from confounding bias in their analyses, omitting the question of the mediation's causality. To the best of my knowledge, only some of these studies try to investigate whether the mediation is causal or not (Hoffmann and Lutz, 2019; Sheikh et al., 2017). Although some other studies use techniques of causal mediation analyses (Friis et al., 2016; Hoffmann and Lutz, 2019; Lastrucci et al., 2019; Sheikh et al., 2017; van der Heide et al., 2013), the majority of studies may suffer from unobserved heterogeneity. This is because they mostly use cross-sectional data and do not employ statistical strategies to eliminate all potential confounding variables. Therefore, further research addressing the causality of the aforementioned mediations is still needed.

4.3 Evidence for the impact of education on health in different ages

In this section, I will concentrate on the variation of the education's effects on health by age. For this purpose, I concentrate only on differences in the effect of education on health within different life stages and do not consider research on the accumulation over time, which contributes to a wider discussion about the accumulation of health inequalities over the life course and cumulative disadvantages (for a review see Dupre, 2008; Lynch, 2003; Lynch, 2006; Mirowsky and Ross, 2008; Pongiglione and Sabater, 2016).

For children and adolescents, there are several studies examining differences in mental health according to children's level of education in school, but few studies on children's overall health or aspects of physical health. This may be because differences in physical health are likely to be less pronounced in childhood than the early effects of education on mental health. The few studies on children's subjective ratings of their overall health, however, indicate that even in children and adolescents, better education is related to more positive health evaluations. For instance, using a sample of secondary school children in Germany and employing growth curve models, Herke et al. (2021) show, that children report different levels of self-rated health depending on the school track attended. In addition, using the same sample for investigation and employing random-effects cross-lagged panel regressions, Kleinkorres et al. (2020) indicate that children's mathematical competence result in more positive evaluations of their health and higher levels of reading skills lead to lower levels in self-rated health one year later. However, they detect no correlation between children's mathematical literacy and reading skills and the number of days that children were absent from school due to illness. Furthermore, in a systematic meta-analysis including about 60 studies, He et al. (2019) found that children's BMI is negatively associated with their academic achievement. Thus, the scarce research supports early effects of education on children's overall health status and BMI.

The studies on the effect of education on mental health aspects in children and adolescents provide additional insights into the early effects of education on health. Empirical evidence suggest that children's academic achievements are associated with mental health conditions and differences in individual emotional states and wellbeing (Bücker et al., 2018; Grant and Brito, 2010). For example, studies suggest that higher levels of academic achievement are associated with conduct disorders or eating disorders (for a review see Grant and Brito, 2010). Additionally, a high number of studies implicates that children's education, e.g. academic test scores and school grades, is associated with their subjective wellbeing, life satisfaction, and emotional states, all of which are highly linked to mental health aspects (Bücker et al., 2018). Thus, these studies additionally support the expectation that, even in earlier life stages, education shapes individuals health.

Based on the high variation in empirical investigations of the causal effect of education on health in middle-aged and older adults, however, empirical studies do not provide a clear age-related pattern. For example, using samples of adults aged 50 and older living in different

European countries in a quasi-experimental design, Brunello et al. (2016) and Fonseca et al. (2020) show strong protective effects of years of education on reporting poor health, diabetes, heart disease, chronic illness, hypertension, arthritis, and lung disease. In addition, using data of elderly people aged 65 and older and employing a twin-fixed-effects regression model, Gatz et al. (2007) suggest a strong effect of years of education on individuals' risks to suffer from dementia. Moreover, comparing the effects of education on health at two different time points using a same sample of individuals born between 1935 and 1965, Dilmaghani (2020) demonstrates that the effects of years of education on self-rated health at older ages are stronger than those predicted at an earlier point in time. Furthermore, Spasojević (2010) suggests strong positive effects of education on a bad health index in a sample of adults aged 36 to 46. In contrast, Kemptner et al. (2011), who concentrates on individuals aged between 45 and 65 living in Germany, show that years of education are only partly related to individual health outcomes, the results suggesting only positive effects of education on health for men concerning the risk of suffering from a long-term illness or working disabilities. Additionally, Braakmann (2011) does not detect any causal effect of years of education on various health measures, e.g. health problems in the last 12 months, physical limitations, chronic diseases, and depressive symptoms, in a sample of adults aged 30 to 40. Based on these studies, empirical evidence does not clearly support the effect of education on health in middle-aged and older adults.

Thus far, empirical research in the differences of the effect of education on health in different age groups indicates that even in childhood and adolescence, education is related to better health outcomes. However, they do not clearly support similar effects for adults, as, depending on the health outcome considered, results show that education may have positive or zero effects on health. This raises the question to what extent education affects different health outcomes in adults. With regard to children and adolescents, the results presented thus far, also generate further questions, as all of the studies presented are strongly limited in their causal inference, and most studies presented may suffer from confounding bias since they could not close all back-door paths linking education to health (Bücker et al., 2018; He et al., 2019; Herke et al., 2021; Kleinkorres et al., 2020). Therefore, although the results suggest strong positive associations, it is unclear, whether these results are also in terms of causality.

4.4 Evidence for a causal effect of education on health

A large number of the studies presented so far raises the question of whether they reflect a causal effect of education on health. While the studies considered in subsection 4.1 and the results for adults highlighted in subsection 4.3 mostly claim a causal interpretation of the coefficients, the studies presented in subsection 4.2 and the empirical studies related to children in 4.3 are predominantly associative. Therefore, this subsection aims to discuss the existing literature in terms of the causal relationship between education and health.

Theoretically speaking, what is the causal effect of education (X) on health (Y)? Based on the counterfactual framework of causality, a causal effect (Δ_i) is defined as the difference between the potential outcomes of Y under a treatment condition (X=1) and control condition (X=0) for the same subject i (see equation (1)) (Gangl, 2010; Winship and Morgan, 1999). The principal idea of this framework is that a subject has an observable outcome in both states and that the difference between the two indicates the causal effect of X on Y.

$$\Delta_i = (Y_i | X_i = 1) - (Y_i | X_i = 0) \tag{1}$$

However, a subject cannot be observed in both states and, thus, testing for causality raises one major challenge in empirical research (for a detailed discussion see Rubin, 1974). Research observes an outcome Y for a given level of X, but not concurrently for the other value of X. Consequently, intra-individual differences in Y cannot be examined under the condition that someone is in state X=1 and X=0 at the same time. Instead, it is only possible to compare group mean differences at time t based on differences in the treatment under investigation, or to observe changes in the same individual at different points in time. Thus, empirical researchers observe heterogeneous treatment effects between units and time points investigated, and consequently empirical studies often show the so-called average treatment effects (ATE), which is the mean difference of Y for all units or time points under the conditions X=1 and X=0 (see equation (2)) (Gangl, 2010).

$$E(\Delta_i) = E[(Y_i | X_i = 1) - (Y_i | X_i = 0)] \tag{2}$$

Yet, given the definition of a causal effect, the differences between groups or time points only represent causal effects if they are exclusively due to treatment and are unbiased to possible confounding factors affecting both the treatment and the outcome. Moreover, they show causal effects if the researcher can argue in favor of the assumptions that the education's effect on health in one individual is independent of the effect in others and that the effect is similar for all units studied (SUTVA) (for detailed information see for example Holland and Rubin, 1987; Rubin, 1974; Winship and Morgan, 1999). Thus, empirical research has to find a methodological approach that allows for the estimation of causal effects considering these conditions.

Methodologically, the ideal solution to this problem is to randomly assign individuals either to condition X=0 (control) or X=1 (treatment), and to investigate differences in the outcomes between the two groups. Randomization allows to eliminate the impact of confounding factors on the estimation of the causal effect and to estimate the true average treatment effect. Therefore, some studies used Randomized Controlled Trials (RCT) to examine the effect of education on health. RCTs use an experimental setting to eliminate important background factors and reverse causality. They randomize individuals to treatment and a control group to ensure, that only the intervention affects the outcome (Galama et al., 2018; Winship and Sobel, 2004). Thus, studies referring to RCTs could estimate the average treatment effect by education.

In a few studies based on randomized controlled trials, empirical results highlight the positive effects of education on health. For instance, one program called the Perry Preschool Program, referring to an early childhood intervention affecting children's level of early education suggests that attending early educational programs positively affects physical health. Individuals of the treatment group had significantly lower levels of dyslipidemia and arterial inflammation in the mid-fifties, and treated female participants showed lower prevalence levels of having diabetes (Heckman and Karapakula, 2019). Furthermore, experimental interventions in schools, implementing health education on various health topics, and health interventions in at-risk groups for various diseases, show that individuals' behaviors and health outcomes changed significantly after such interventions. For instance, Wang et al. (2018) highlight that children exhibit reduced levels of body mass index, waist circumference, systolic blood pressure, or total cholesterol after an educational intervention, while Brown et al. (2013) suggest that educational interventions reduce the risks for myocardial infarction, revascularization, and hospitalization. Thus, these RCTs suggest positive causal effects of education on individuals' health.

However, although randomized controlled trials are the gold standard in causal research, the studies mentioned also have some limitations: due to practical and ethical reasons, for instance, they only focus on specific types of interventions in education and cannot test the causal effect of general education or formal schooling on health. Therefore, they do not answer the question of whether education, as defined in subchapter 2.1, would produce positive effects on health. The experimental designs assigning individuals' to early childhood education also only rely on a very small and selective sample that is based on, for example, children with lower levels of cognitive abilities from deprived families, and partly includes intervention related to individual health-related behavior. Thus, it is disputable whether the observed effects are also valid for the general population and truly based on the educational intervention (Galama et al., 2018). As a result, even though they are of high value in political contexts and for empirical literature, given these limitations these studies do not sufficiently answer the question of whether education affects health.

Based on the limitations of RCTs, a large number of studies addressing the causal effect of education on health relies on observational data for causal analyses. Yet, observational data is not explicitly generated using randomization. This generates the challenge that the treatment and the outcome will be correlated based on other factors, while the standard estimator is usually inconsistent. As a result, in order to investigate the causal effect of education on health, empirical investigations mostly depend on alternative strategies to estimate the true causal effect of education on health (for a detailed overview see Listl et al., 2016).

One such alternative strategy for studying the causal effect of education on health using observational data employs twin studies. Such studies predict the education's impact on health by employing twin-fixed-effects regression models, only using the within-pair variation in education and health. They thereby claim to eliminate unobserved confounding variables based on genes and shared family environments. However, twin data does not directly support the positive effect of education on health, as various twin studies suggest that this effect is largely confounded by genetic and family characteristics. For example, Amin et al. (2015), Fujiwara and Kawachi (2009), Gerdtham et al. (2016), Halpern-Manners et al. (2016), Lundborg (2012), and Seglem et al. (2020) indicate that the effects of years of education or the highest educational certificate obtained in life is not statistically significantly different from zero for health outcomes, such as BMI, waist circumference, waist-hip-ration, depression, panic-phobia, somatization, sickness absence, or self-rated health. Only some studies contradict these results by presenting a small positive impact of education on self-rated health, and negative effects on cardiovascular disease, dementia, or chronic health conditions (e.g. Amin et al., 2015; Fujiwara and Kawachi, 2009; Gatz et al., 2007; Madsen et al., 2014; Monden, 2010). As a result, most twin studies suggest a confounded relationship between education and individual health status.

However, twin studies raise concern whether the design is adequate to examine the causal effect of education on health. The strength of this approach lies in the elimination of confounding of genetic and shared family characteristics, however, they are mostly limited to the negligible variation in education between twins (Galama et al., 2018). In addition, investigating between twin-variation does not guarantee causality, since the differences between twins' education might be due to systematic differences between the two (McAdams et al., 2021; McGue et al., 2010). Furthermore, twin studies focus on a special subgroup that is shown to be significantly different from the general population (McAdams et al., 2021), thus lacking external validity. As a result, Galama et al. (2018) conclude that they do not sufficiently estimate the causal effect of education on health for the general population.

For this reason, other studies use observational data by employing quasi-experimental designs to identify the causal effect of education on health. These empirical investigations use random assignments to education based on the exogenous variation in education, and most of them refer to compulsory schooling reforms to construct a quasi-experimental design in which individuals are randomly assigned to different years of education (Galama et al., 2018; Hamad et al., 2018). However, a few other studies published used exogenous variation by, for example, school fees, the expansion of school types, or Vietnam War draft rules (e.g. Jürges et al., 2011; Reinhold and Jürges, 2010; Walque, 2007). Regarding the effect of education on health, they show a wide variation within their results (Hamad et al., 2018). For instance, some studies highlight that one additional year in education positively affects individuals' self-rated health status, hypertension, mental health, functional abilities, and sexual health, while others indicate that additional years of education prevents cancer or obesity. However, there are also studies which contradict these positive effects, instead indicating that education increases the risk of being obese. Another substantial body of research shows that years of education do not affect all of the different indicators of health already mentioned (for a detailed review see Hamad et al., 2018). Therefore, given the wide range of estimates, for quasi-experimental studies, it is unclear whether or not years of education positively affect health or whether this effect relates only to some measures.

The aforementioned inconclusive results of the quasi-experimental studies raise further questions about the strength and weaknesses of previous research. Although quasi-experimental designs provide the opportunity to investigate the causal effect of education on health in general populations, they may be limited in the overall conclusiveness of previous results. For example, although all studies investigate the effect of years of education on health, they refer to different subgroups depending on the quasi-experimental design employed. This makes them less comparable and results in different conclusions concerning the effect of education on health (Hamad et al., 2018). Furthermore, quasi-experimental studies require strong assumptions about the effects of the exogenous variation used. They have to assume that the event used as the quasi-experiment caused random assignment to educational levels, but this assumption is empirically not falsifiable (Hamad et al., 2018). Therefore, depending on the validity of the underlying assumptions, the results may be biased due to unconsidered specifics of the event used which are associated with selection processes into different levels of education and health. Similarly, the results of previous studies may be biased because most of these studies could not directly observe individual differences in education caused by exogenous variation, instead relying on the assumption that the event also had the expected effect, and adjusting the information on education up to a certain point according to these expectations. For example, they adapt the available information on years of education according to the assumed differences before and after a school reform (see for example Brunello et al., 2016; Davies et al., 2018; Kemptner et al., 2011), thus, relying on the hypothetical effects of an event on education. This might lead to skewed estimates if the assumed changes are not observable to the same degree in reality due to unexpected variation in educational trajectories, or discrepancies between the political regulation and implementation of a reform in practice. Finally, those studies may suffer from limitations in sample size or very weak effects of the exogenous variation employed on education. This leads to skewed inference statistics because such designs have high demands of statistical power and require strong effects of the event on education for statistical analyses (Hamad et al., 2018). Thus, based on biased statistical inference some studies might indicate false zero, positive or negative effects of education on health, and depending on the reform used, methodological challenges and data limitations possibly limit their inferences about the effect of education on health (Hamad et al., 2018; Xue et al., 2021).

Despite the wide range of studies using one of these three different approaches, there is also literature which uses cross-sectional or panel regression analyses to investigate the effect of education on health outcomes. For instance, a large number of studies investigates the education's effects on health in OLS and logistic regression models, accounting for confounding factors to predict the effects of education on health (Lynch and Hippel, 2016). These studies consistently show educational differences in various indicators representing individuals' physical and mental health status and daily functioning (for a review see Cutler and Lleras-Muney, 2006). However, by using individuals' fixed-effects to eliminate time-constant confounding variables and accounting for time-varying factors, Lynch and Hippel (2016) indicate that, for example, completing a high school degree does not affect individuals' subjective evaluations of their overall health status. Accordingly, based on these results, a clear statement about the causal effect of education on health is not possible.

Although cross-sectional and fixed-effects panel regression models contribute toward identifying the effect of education on health, they contain limitations which only make it conditionally possible to determine the causal effect in the proper sense previously defined. First, cross-sectional regression models are most likely biased by unobserved confounding factors. Although most studies aim to control for the most important factors, there may still be unobserved heterogeneity that biases the results. Similarly, fixed-effects regression analyses are possibly biased by time-varying unobserved factors. However, since they eliminate time-constant confounding variables, fixed-effects regression analyses could be a valuable strategy to more closely approximate a causal interpretation of predicted estimates in populations where education changes.

To conclude, although a substantial amount of research exists on the effect of education on health, design- and method-based limitations restrict the results, and further research addressing these limitations is necessary. Depending on the method employed, the results indicate either positive, zero, or negative effects of education on different health outcomes. While some studies using randomized controlled studies consistently show positive effects of (health-related) education on health, twin studies and fixed-effects panel regressions suggest the opposite. Furthermore, quasi-experimental studies show no clear pattern. Therefore, further research should address the limitations of these studies and investigate how the given limitations affected previous estimates to find out whether or not the effect of education on health is truly causal (Galama et al., 2018; Hamad et al., 2018).

4.5 Main contribution of this dissertation project

The aforementioned state of research highlights several limitations and research gaps related to the causal effect of education on health that encourage further work in this field. Firstly, the existing empirical studies highlight variation within the effect of education on health, depending on the measurement of education and health used. However, systematic analyses on these differences in terms of, for example, replication studies or direct tests referring to the differences in the relationship, are still lacking. Secondly, some limitations and research gaps in studying the indirect effects of education on health raise questions about the relevance of theoretical mechanisms. Particularly for the mediation effects of health-related knowledge, social, and psychological resources, the small number of studies narrows the empirical evidence. In addition, the lack of causal analyses generates concerns about whether unobserved heterogeneity biases predicted mediations. Finally, investigations of the causal effect of education on health suffer from methodological and data-related limitations, which should be addressed in further research based on different data sets and methods.

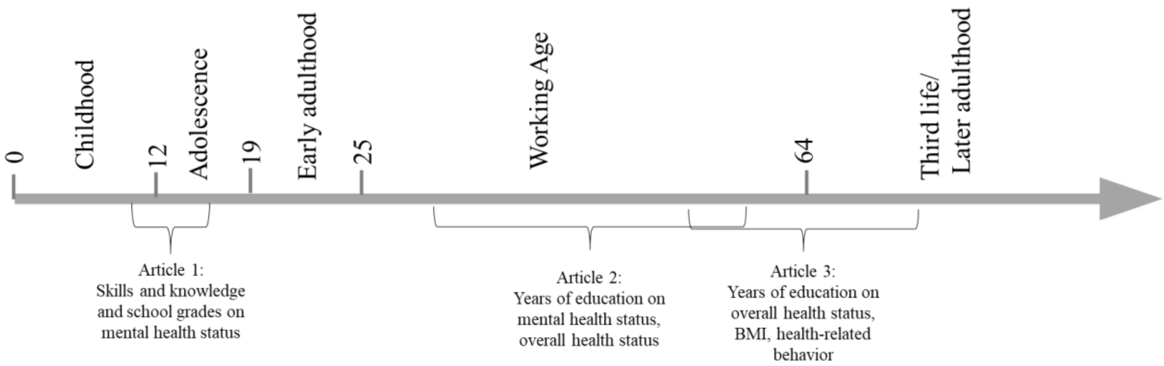
Comprising three different studies, this thesis contributes to some of the aforementioned methodological and content-related limitations and research gaps (for an overview see Table 1). First, I devote attention to ***methodological challenges*** in identifying the causal effect of education on health. In doing so, I strongly focus on causal inference and aim *to identify causal effects* in all studies conducted addressing the methodological challenges of prior research to approximate a causal interpretation of the effects mentioned. In Article 1, I focus on the lack of causal inference of education's effect on health in childhood and adolescence. By using fixed-effects panel regression models, I eliminate important time-constant confounding factors to come closer to a causal interpretation of the predicted estimates. In Article 2, Sebastian Prechsl and I employ causal mediation analyses and robustness checks addressing unobserved heterogeneity in our results to provide a more strongly causal interpretation of our results. Together with Guido Heineck, I address the methodological and data-based limitations of Kemptner et al. (2011), who examined the causal effect of education on health using exogenous variation introduced by a compulsory schooling reform in Germany. In doing so, we investigated, how the operationalization of the instrument and data limitations affect the results (Article 3, see Chapter 4). Since the study of Kemptner et al. (2011) suffers from several data limitations such as missing information about starting and ending dates of education and the federal state of schooling, thus providing imprecise measurements of the effect of the compulsory schooling reform on individuals education, Article 3 transcends some of these limitations and highlights how assumptions made by the researcher affect causal inference.

Along with the special focus on causal inference, I also address *differences in the effect of education on health by the measurements of the two concepts*. For example, in the first paper, I address systematic differences in health by the knowledge-related dimension and the signals provided by education (see Article 1, Chapter 2). In this article, I examine the differential impact of individuals' skills and knowledge (operationalized by different levels in math and reading competencies) and of educational signals (represented by school grades) on the mental dimension of health, as measured by individuals' life satisfaction. In addition, together with Sebastian Prechsl, I focus further on differences between the effect of education on mental health and individuals' evaluations of their overall health status (see Article 2, Chapter 3). While the main interest of this paper concerns the subjective evaluations of individuals' mental health, we also replicate our results for overall health status. Furthermore, complementing the prior research in Germany conducted by Kemptner et al. (2011), the study with Guido Heineck replicates results of their quasi-experimental design with regards to the subjective evaluation of the overall health status (see Article 3, Chapter 4). While the previous study considered the effects of education on long-standing diseases, functional limitations, and BMI, we complement this by addressing an overarching health measure.

Second, this dissertation project enters the discussion of the ***relevance of mechanisms*** linking education to health. Complementing the scarce literature on the mediation of the effect of education on health through social resources, this thesis includes an analysis for the mediation effect of social relationships. Together with Sebastian Prechsl, I investigate the education's indirect effect on individuals' evaluations of their mental and overall health status via their overall level of social integration, and differences in the number of weak and strong social relationships (see Article 2, Chapter 3). In doing so, we address some limitations of previous research by employing techniques of causal mediation analyses and by testing for confounding in separate robustness checks for a subset of our analyses. In addition, we contribute to the literature by examining the mediation effect separately for each type of social relationship and replicate the mechanism analyses for individuals' subjective evaluation of their overall health status.

Finally, this dissertation project aims to contribute to the issues related to ***variation by age*** by examining the effect of education on health in different age groups (see Figure 14 for a graphical illustration). Motivated by the theoretical assumptions suggesting differences in the effect of education on health by individual age, this dissertation projects investigates the causal effect in children and adolescents, middle-aged adults, and older people. Firstly, I explore the effects of two different dimensions of education in a sample of children to scrutinize whether education is causally related to health even in younger ages (Article 1, see Chapter 4). Secondly, I investigate the mediation effect of social relationships in middle-aged adults to shed more light on the effect of education on health in the working-age population (Article 2, see Chapter 3). Finally, together with Guido Heineck, I focus on older individuals between the ages of 48 and 71 to investigate the long-term effects of education on health (Article 3, see Chapter 2).

Figure 14: Overview of the Age Group Studied by the Three Articles



Source: Own illustration.

To sum up, with respect to its main contributions, this dissertation project pursues the following research agenda (for an overview see Table 1): a first study (Article 1) examines the relationship of different dimensions of education on children's mental health, thereby directly contributing to the discussion on the causal relation of childhood education to health and offering deeper insights into the relevance of education's different dimensions on health. A second study (Article 2) concentrates on empirical analyses of the mediation effect of social relationships within the education-health relationship. It provides further investigation into the potential relevance of social resources for the link between education and individuals' overall mental health in working-age adults. The third study (Article 3) examines the causal effect of education on health in older people by employing exogenous variation in compulsory schooling during the mid-20th century in Germany in a quasi-experimental design. It addresses some methodological and data-related limitations of previous results published by Kemptner et al. (2011) and tests for the heterogeneity of results by the empirical strategy used for statistical analyses.

Table 1: Overview of the Articles

Article	Authors / Share	Year	Title	Journal / Status
1	Kroh, J. / 100%	2021	The impact of children's academic competencies and school grades on their life satisfaction: What really matters?	Published in *Child Indicators Research*[1]
2	Kroh, J. / 70% Prechsl, S./ 30%	2021	The intervening role of social relationships in the effect of education on mental health	Not submitted
3	Kroh, J. / 70% Heineck, G. / 30%	2020	Revisiting the Causal Effect of Education on Health	Not submitted

Source: Own Illustration.
1 Published under Lettau, J.

5 Research designs

To conduct the research mentioned, this dissertation project uses different data sets, operationalizations and methodological approaches. This chapter describes the specific characteristics of the individual studies, discusses challenges in the estimation of the causal effect of education on health and summarizes solutions provided by the three articles (for an overview see Table 2).

5.1 Data and samples

This dissertation project focuses strongly on longitudinal and panel data providing rich information on individuals' education, different dimensions of health, and theoretical mechanisms. However, in order to investigate the causal effect of education on health in different life stages by focusing on the three different contributions, all three articles use different data sets and samples for empirical analyses (for an overview see Table 2). Thus, the following section provides insights into the data sets used and highlights both their strengths and limitations for empirical investigations.

For the investigation of education's effect on mental health in children, Article 1 uses data of a sample of secondary school students drawn from regular and special-needs schools in Germany and provided by the National Education Panel Study (NEPS SC3) (for detailed information about the survey design and sampling strategy see Blossfeld and Roßbach, 2019). This unique and novel dataset on children offers longitudinal information about children's educational trajectories as well as repeated measures of academic competencies, school grades, and different health-related outcomes. Students are observed annually either in the school context or at home. Thus, the NEPS SC3 allows for panel analyses of the effect of different aspects of education on children's health, and enables testing theoretically expected differences in the relevance of skills and knowledge levels and educational signals on children's mental health by providing repeated measurements of academic competencies (skills and knowledge), school grades (signals), and life satisfaction (mental health). In addition, since the NEPS SC3 refers to students in different types of schools it provides the opportunity to consider the educational context in empirical analyses. The NEPS SC3 thus permits deeper insights into the effect of education on health by taking into account the school track attended.

Despite these advantages, the NEPS SC3 also features some data limitations, which cause some restrictions in the study. First, the NEPS SC3 only provides repeated measurements of academic competencies for children observed in the school context. Thus, children who left the school observed by the NEPS, or attended a school that refused further cooperation with the survey institute, are not available for analysis. This restricts the analyses presented in Chapter 2 to children without any change of school environment. Hence, the sample very probably contains children with continuous educational trajectories, as well as intermediate levels of academic achievement and school grades, because children with extremely high or low levels of academic competencies and school grades are more likely to change the type of school during the observation period. Therefore, in this case, the estimates of the empirical analyses should be considered as lower bound estimates. Second, parental information is only available for some parts of the sample, which restricts the opportunities to control for a number of time-varying background characteristics and family-related events affecting children's educational outcomes and health (for a detailed discussion see Chapter 2). Consequently, although the NEPS SC3 is the first study which allows for analyses that approximate the causal effect of education on health in children, it has some limitations which must be considered.

To investigate the mediation effect of the characteristics of individuals' social relationships in the education-health relationship, Sebastian Prechsl and I used data of the Panel Study Labour Market and Social Security (PASS) of the Institute for Employment Research (IAB). For this study, the PASS is particularly well-suited, because it includes a wide range of repeated measurements about individuals' social relationships and health status. This allows us to consider the time-related variation in individuals' social networks and health in empirical analysis, and offers the opportunity to test whether time-constant individual characteristics undermine some part of the relationship. In addition, since the PASS includes a subsample referring to households receiving welfare benefits (so-called Unemployment Benefit II) and, thus, offers data even for those with the lowest levels of education, the PASS helps to avoid the underestimation of education's effect on health due to education-related selectivity processes during the observation period.

However, although the PASS is a rich data set and is highly suitable in Germany both for the investigation of the mediation effect in middle-aged adults and for the approximation to a causal interpretation of the effect, there were some data-related challenges, which we had to address in our study. First, although the PASS provides rich information on social relationships, information about wider networks (weak ties) is only given by the active memberships in voluntary associations and indicates whether someone participates in a labor union, a political party, a church congregation, sports, music, or cultural club, or an association of another kind. However, it does not provide detailed information about the exact number of voluntary associations in which someone participates. In addition, further information on wider networks is missing. It therefore remains unclear to which extent someone is a part of other types of weak ties not represented by the active membership in voluntary associations, such as work-related networks. Thus, the actual number of weak ties is not observable. As a result, despite the benefits of the PASS data, my Co-Author and I discuss these limitations of the measurement of the number of weak social relationships in the final section of the study.

To investigate the causal effect of education on health in older people based on a quasi-experimental design, Article 3 relies on data of the Starting Cohort Adults of the National Educational Panel Study in Germany (NEPS SC6) (for detailed information about the survey design and sampling see Blossfeld and Roßbach, 2019). The NEPS SC6 is well-suited for this investigation for two reasons: firstly, because it provides detailed biographical information about educational trajectories asking respondents for starting and ending dates of their schooling episodes and the place of schooling. This enables a precise identification of affected individuals by the compulsory schooling reform and permits robustness checks of the quasi-experimental design, which were not possible in previous studies. Secondly, NEPS SC6 provides various numbers of health indicators measured in waves 4 and 7, which allows for the estimation of education's causal effects on different dimensions of health and health-related behavior. This not only provides further evidence on the variation of education's effects on health based on methodological aspects, but also contributes to the ongoing discussions about different effects based on the operationalization of health. Furthermore, the NEPS contains individuals born between 1944 and 1986 as well as an adequate number of respondents, which are at least 55 at the time of the corresponding survey waves; this allows for a focus on older adults.

Despite the benefits of the NEPS SC6 which help to overcome prior limitations, we faced some data limitations in our empirical analysis, which required special attention in the study. First, respondents were asked for the starting and ending dates of educational episodes, retrospectively. Thus, recall errors caused some measurement errors in educational trajectories, which prompted us to exclude respondents with extreme values of education from our analyses in order to reduce the measurement bias in the duration of schooling. Second, based on the sampling strategy, we do not observe variation in compulsory schooling in federal states with changes before 1950. Therefore, we restricted our analyses to federal states that expanded their compulsory schooling after 1950 to concentrate only on German regions with observable variation in compulsory schooling in NEPS SC6. Third, the NEPS SC6 suffers from health-related panel mortality, which leads to a selection of the healthiest individuals within the panel, this may result in an underestimation of the causal effect of education on health. Finally, due to the sample restrictions, we were left with about 2,800 cases, which may limit the statistical power of the empirical models leading to biased inference statistics (for detailed descriptions on the sample, see Chapter 2). Hence, although we argued for the high benefits of the NEPS SC6, we considered these limitations in the interpretation of our results.

To sum up, both strengths and limitations of the data used in the three empirical analyses highlight the need for a high level of data quality to investigate the different facets of the effect of education on health. Although all data sets provide rich panel data and longitudinal information on individuals' education, health, and related mechanisms, they all show weaknesses limiting the empirical results of the three articles. As a consequence, although this dissertation project takes advantage of these rich data sets, some limitations restrict causal inference and the validity of the results.

Table 2: Overview of the Research Designs

Article	Data set	Sample definition	Dependent Variables	Independent Variables	Methods
1	NEPS SC3, waves	children aged between 10 and 15	Overall life satisfaction	Academic competencies in reading and mathematics Grade point averages	Fixed-effects panel regression models with heterogeneous effects by school track, sensitivity analyses for gender differences
2	PASS, waves 1 to 12 (2006/2007 to 2018)	adults aged between 30 and 65	At least good mental health	Years of education *Mediators:* Married or cohabited Number of close relatives and friends outside the household Active membership in voluntary associations Social integration index	Linear random-effects panel regression model with wave fixed-effects , Mediation Analyses following Baron & Kenny (1986) and VanderWeele (2015), Test of significance of the mediation proposed by Sobel (1982)
3	NEPS SC6, waves 4 (2011/2012) & 7 (2014/2015)	adults aged between 48 and 73	Poor health Body Mass Index Being obese Having overweight Current smoking Having quit smoking Regular alcohol consumption Being physically active	Years of education	Quasi-experimental design using the expansion of compulsory schooling from 1949 to 1969 for exogenous variation, instrumental variable approach with two stage least square estimation, replication of the strategy used by Kemptner et al. (2011)

Source: Own illustration.

5.2 Operationalization of education

While all three articles employ education as the main independent variable, they refer to different operationalization of education. For example, in Article 1 I investigate the effect of children's skills and knowledge levels, and educational credentials on their mental health. In doing so, I firstly scrutinize the effect of individual skills and knowledge levels on health more directly, focusing on children's actual *academic competence levels in reading and mathematics*, which both provide multidimensional measurements of individuals skills levels. I refer to newly developed longitudinal tests including a maximum of 33 items. For empirical analyses, I used uncorrected weighted maximum likelihood estimates of individuals' competence levels as suggested by van de Ham et al. (2018). Secondly, I examine whether education-related signals affect children's mental health, using a combined *mean of final grade point averages* in German and Math of the previous school year. These averages do not only indicate children's performance levels in school but also serve as signals of educational success or failure (Lekholm and Cliffordson, 2008; Willingham et al., 2002). I relied on children's self-reported school grades, which, despite of some limitations, serve as a good indicator for educational signals in secondary schools (for detailed discussion see Chapter 2). In addition, I used the information of the previous school year to consider time-lagged effects on individuals' life satisfaction. As a result, Article 1 reveals the effect of children's skills and knowledge levels, as well as education signals, on life satisfaction.

To examine the indirect effect of education on health via individuals' social relationships, Sebastian Prechsl and I focus on individuals' *years of education* considering the highest level of general and vocational education. For this purpose, we use a generated variable which reflects the *hypothetical years of education* depending on the highest educational certificate obtained. This variable captures not only acquired skills and knowledge, but also encompasses signaling attributes of education and associated social status. In addition, we consider both general and vocational education to better reflect the number of educational institutions attended. Therefore, Article 2 investigates the effect of education on health concentrating on individuals general and vocational education levels measured by the hypothetical time spent in these educational settings.

To analyze the effect of education on health in older adults, Article 3 also examines the effect of years of education. However, in contrast to Article 2, Article 3 focuses on the effect of *calculated years of general education* referring to the actual time spent in general educational institutions. This is because the exogenous variation employed affects compulsory schooling and, thus, provides a causal estimate for the effects of individuals' general educational levels on health. For this purpose, we use starting and ending dates of schooling episodes in primary and secondary schools only, considering typical pathways in the general education system (for further details see Chapter 4). Assuming that with each year in education additional skills and knowledge are acquired, this indicates the different levels of skills and knowledge acquired in these educational settings. However, *calculated years of schooling* do not necessarily reflect educational credentials, since they include individuals' class repetitions and differences in the length of school years. Thus, Article 3 most likely represents the causal effect of individuals' skills and knowledge levels on health, as acquired in education.

5.3 Operationalization of health

For measuring health, all three articles focus on individuals' subjective ratings of their health. Given the high variation within health-related measurements, this dissertation project aims to primarily contribute to the effect of education on people's evaluations of their mental and overall health status. For instance, Article 1 focuses on children's evaluations of mental health aspects, because in childhood and adolescence, physical health differences due to education levels are improbable. Although children may well differ in the state of their physical health, it seems unlikely that education shapes their physical health in these early stages (Lynch, 2003). Instead, components of mental health are important in childhood and adolescence, and empirical evidence suggests a strong relationship of these components to education (Bücker et al., 2018), which is why I concentrate on individuals' mental health status. In doing so, I use children's evaluations of their life satisfaction to examine the early effects of education on mental health. Differences in children's life satisfaction are strongly associated with mental health problems later in life, and, thus, serves as an early indicator of mental health differences (Gilman and Huebner, 2003; Park, 2004). In the evaluations, I employed the question: "How satisfied are you currently and in general terms with your life?", which constitutes a well-established indicator in life satisfaction research (Cheung and Lucas, 2014; Frey and Stutzer, 2002; Jovanović, 2016; Kahneman and Krueger, 2006). The scale ranges from 0 "completely dissatisfied" to 10 "completely satisfied" and I included the measurement as a metric variable in the analyses.

As in Article 1, Sebastian Prechsl and I also focus on individuals' mental health status in Article 2. Although theoretical arguments suggest the relevance of social resources in all health dimensions, it seems more likely that they explain a larger part of the effect of education on mental health. This is, because social relationships reduce individuals' daily distress, provide emotional support, and stabilize their self-esteem and self-worth, all of which are all highly associated with better mental health outcomes. Thus, to complement the existing research, we investigate the mediation effect of social relationships for the education's effect on mental health. We use an individual's subjective evaluation of their mental health by way of the question: "How strongly have you been affected by mental problems, such as fear, dejection, or irritability in the past 4 weeks? Please tell me whether you were affected 'not at all', 'a little bit', 'moderately', 'quite a bit' or 'extremely'?" We constructed a binary indicator reflecting "*at least good mental health.*" In sensitivity analyses, however, we also investigate the effects on individuals' evaluations of their overall health status to check whether the same conclusions could be reached if we refer to a broader measurement of health. We here employ the question: "How would you describe your state of health in the past 4 weeks in general?" with values ranging from 1 "very good" to 5 "very poor". In analogy to our evaluation of mental health, we recoded the variable and build a dummy variable indicating reporting "*at least good overall health.*" Thus, Article 2 provides deeper insights into the effect of education on individuals' evaluations of mental and overall health.

In contrast, Article 3 concentrates on the several dimensions of individuals' physical and overall health. Additionally, it includes health-related behaviors, which are important determinants of individual health status. We investigate the causal effect of individuals' *evaluations of their overall health status* by referring to the question: "How would you describe your general state of health?", which requests for an evaluation of individuals health status ranging from 1 "very good" to 5 "very poor". This measurement strongly correlates with chronic conditions and diseases that are accompanied by physical constraints and problems with daily performance. In addition, it is moderately associated with individuals' mental health (Abdulrahim and El Asmar, 2012; Chandola and Jenkinson, 2000; Krause and Jay, 1994; Lundberg and Manderbacka, 1996; Singh-Manoux et al., 2006). For the empirical analyses, we recoded the question to indicate whether a person reported poor health, with a "0" assigned to people who reported at most mediocre health and a "1" used for all respondents who reported poor or very poor health. However, although self-rated health has shown itself to be a good and valid indicator for individuals' overall health status, it also contains some limitations, which are partly considered in this thesis. For instance, individuals' self-reported health status only weakly correlates with their physical constitution (Imai et al., 2008; Singh-Manoux et al., 2006). Thus, to maximize the impact of this thesis my Co-Author and I address the causal effect of education on individuals' BMI, and estimate the risk of being obese or having overweight in Article 3. Finally, we investigate the causal effects of education on individuals' smoking habits, alcohol consumption levels, and physical activity to also consider effects on important mechanisms in the education-health relationship.

5.4 Identification of causal effects

In order to determine the causal effect of education on health at different ages while taking into account the different educational dimensions and the mediation of the effect by the number of social relationships of individuals, all three studies follow the basic principles of causality as briefly described in subsection 4.4. Therefore, they all consider the selection processes discussed in subchapter 1.3 and use different techniques to avoid confounding bias based on important factors affecting both education and health. Thus, different statistical methods are employed to avoid bias by unobserved heterogeneity.

As a first technique to partly eliminate unobserved heterogeneity in the effect of education on health, I take advantage of fixed-effects panel regression models (see Articles 1 and 2). Although the more sophisticated strategies, such as randomized controlled trials and quasi-experimental designs presented in subchapter 4.4, are highly recommended for causal inference, I was not able to apply them to all analyses. For example, for Article 1 and Article 2, a random assignment is necessary to different interventions affecting different dimensions of education and the mediators at the same time. For instance, the investigation of the effects of different dimensions of education on mental health requires different randomization to interventions of which one affects children's competence levels and another affects their school grades. Similarly, to identify the causal effect of education on health in the working-age population by considering mediation of the number of social relationships, one intervention would be required which affects individuals' education, and one which affects their social relationships. However, to the best of my knowledge, there is no experimental design available to employ these kinds of analyses in the respective populations. Thus, I used alternative strategies for causal inference by taking advantage of fixed-effects panel analyses.

Compared to cross-sectional regression analyses, fixed-effects panel analyses perform somewhat better by addressing the problem of unobserved heterogeneity at least in part, because fixed-effects estimation is based on an error component model which splits up the error term into two different components (see equation (1)). α_i contains stable characteristics corresponding to one subject i observed and ϵ_{it} reflects the idiosyncratic error term that varies by observation t and unit i (Brüderl and Ludwig,2015).

$$y_{it} = X_{it}\beta + \alpha_i + \epsilon_{it} \tag{1}$$

In panel regression models, individuals are repeatedly observed over time, and previous observations of an individual act as their own controls in the estimation strategy. The values of an outcome Y before the treatment are compared to values of the outcome after the treatment. By demeaning the data (see equation (2)), they eliminate the variation between subjects and extract only the variation within a subject i over time (Brüderl and Ludwig, 2015). This enables the estimation of intra- individual changes in the outcome based on changes in the treatment by leveling out any time-constant confounding variables. Thus, bias due to time-invariant individual confounding factors on education and health should be eliminated (for a detailed discussion see Brüderl and Ludwig, 2015).

$$y_{it} - \bar{y_i} = (X_{it} - \bar{X}_i)\,\beta + \epsilon_{it} \tag{2}$$

Although fixed-effects regression models eliminate time-constant confounding factors, they cannot avoid bias through time-variant factors. Since they estimate changes in the outcome based on intra-individual changes, these models underlie the assumption of "temporal homogeneity" meaning that nothing relevant changes except for the treatment (Brüderl and Ludwig, 2015). The assumption, however, is only valid, if important time-variant confounding factors are controlled. Consequently, if some of these factors are unobserved, the fixed-effects panel regression still renders biased results.

Therefore, following the aforementioned idea, I estimated the effect of children's competence levels and school grades on life satisfaction by using fixed-effects panel regression models in Article 1. I take advantage of the comparison of individuals' life satisfaction by changes in their competence levels and school grades to investigate the effect of education on mental health. Based on the assumption that important time-constant factors, such as family characteristics and genes, are eliminated by the estimation strategy, I only control for time-variant characteristics, which are expected to affect both education and the mental health measurement. In addition, I consider the heterogeneity of the effects of academic competencies and school grades on life satisfaction by school track attended and gender to evaluate whether the predicted estimates yield the same conclusions in specific subgroups.

Likewise, in Article 2, Sebastian Prechsl and I also take advantage of fixed-effects regressions, albeit only in parts of our analyses. This is because in contrast to the study including children, we observe only small changes in individuals' education during middle-aged adulthood. Consequently, in a fixed-effects model, the effect of education on health would be eliminated because of its time invariance, prompting us to mainly focus on the random-effects approach to estimate educational differences in health, which, however, relies on stronger assumptions than the fixed-effect estimator (for detailed information see Chapter 3). In doing so, we had to include time-variant and time-invariant confounding factors available in the data set used in our analyses. However, we could not include important personal characteristics, since they are not measured in PASS. For the estimation of the effect of social relationships on health representing the second part of the chain of mediation, we were able to employ a fixed-effects regression model, allowing us to verify whether the expected positive effect of social relationships on health is robust to the elimination of all time-constant variables.

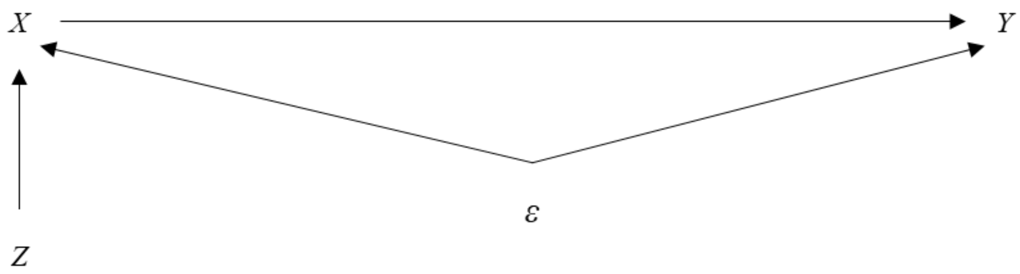
However, it must be emphasized that fixed-effects panel regression models are still limited in estimating the causal effect of education on health, as they may be biased by time-varying unobserved heterogeneity since they only eliminate time-constant confounding factors. Thus, the estimates might be inconsistent regarding the causal effect of education on health. Moreover, only effects of time-varying treatments can be estimated, which require an intra-individual variation over time in order not to eliminate the effect of interest. Therefore, for the effect of education on health, such models require variation in education, which refers only to specific subgroups, such as children and youth in schools, trainees, or individuals in further education. Consequently, for the last study of this thesis, another strategy must be employed to identify the causal effect of education on health in older adults.

For this reason, my Co-Author and I use a well-established quasi-experimental design to investigate the causal effect of education on health for older adults in Article 3. In line with Kemptner et al. (2011), we exploit exogenous variation introduced by the expansion of compulsory schooling (C9-reform) and examine individual differences in health caused by a quasi-randomly assignment to different lengths of compulsory schooling in the mid-20th century in Germany. Initiated by the C9-reform, federal states in Germany extended compulsory schooling from eight to nine years between 1949 and 1969 (Helbig and Nikolai, 2015), resulting in exogenous variation in the time attending school (for a detailed description, see Chapter 4). Therefore, we follow the idea of previous research that the reform serves as a quasi-experimental design, which introduced a random assignment to different durations of education.

To investigate education's effect on health by using a quasi-experimental design, we use the reform as an instrumental variable to eliminate unobserved confounding factors. An instrumental variable Z is assumed to identify a causal effect of X on Y if the following five conditions hold (Angrist et al., 1996): firstly, the instrument must cause significant changes in the treatment (X) (nonzero effect of Z) and, secondly, the potential outcome of one subject cannot depend on the treatment status of others (SUTVA). Thirdly, Z must randomly assign subjects either to the treatment or the control group. Fourthly, any effect of Z on Y must be due to the changes in X (exclusion restriction, see Figure 15). Finally, Z causes changes in X in the same direction, i.e. no one reacts to the opposite (monotonicity assumption). Therefore, if these assumptions hold, Z could identify the average causal effect of X on Y.

Based on the aforementioned underlying assumptions, the causal effect of X on Y depending on Z can be written as $y_i\left(1, Z_i(1)\right) - y_i\left(0, Z_i(0)\right)$, which is the difference between the average level of y_i conditioned on the assignment to the treatment and the average level of y_i for the untreated. This can be rewritten as $\left(y_i(1) - y_i(0)\right) \cdot (Z_i(1) - Z_i(0))$ and refers to the weighted average causal effect based on the proportion of treated and untreated subjects. However, since in reality, there are subjects who do not respond to the instrument (never-takers and always-takers), this causal estimator refers only to a local average treatment effect, reflecting only the effect of those who reacted to the assignment (Angrist et al., 1996; Imbens, 2014).

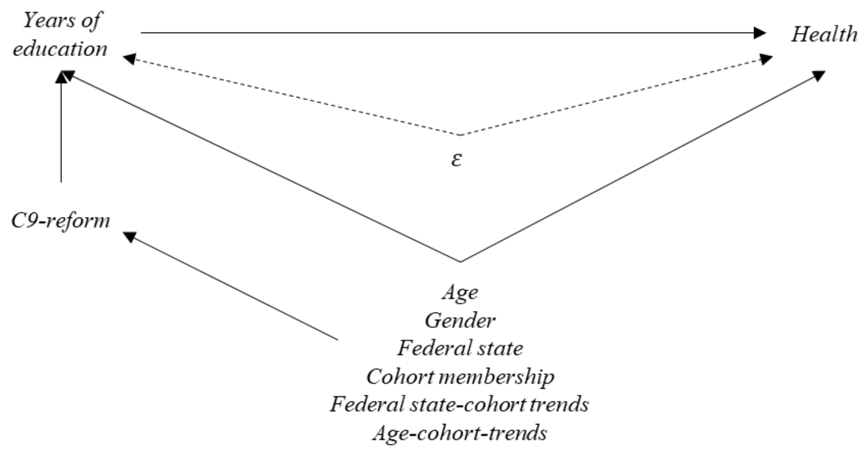
Figure 15: The Principles of an Instrumental Variable



Source: Own illustration based on Angrist et al. (1996), Brito and Pearl (2012).

Using the C9-reform as an instrument, different specifics of the reform have to be taken into account. We had to demonstrate whether the assumptions hold for a causal interpretation of the effect of education on health based on the reform, which led us to investigate whether the reform affected individuals' education levels. In addition, we checked the consistence of our results, if our sample is constricted to the compliers only and conditioned our instrumental variable on some covariates which limit the exogeneity of the instrument (see Figure 16). Finally, we tested whether another concurrent school reform and its consequences biased our results.

Figure 16: C9-Reform as a Conditional Instrument for Education in the Education–Health Relationship



Source: Own illustration.

By using the C9-reform as an instrument for education, we conducted a two-stage least square estimation (2SLS) to estimate the local average treatment effect of years of education on health. The two-stage least square estimator estimates the causal effect in two steps, first assessing the effect of the instrument Z on the treatment X (see equation 3) and then identifying the causal effect of the treatment on the outcome Y by using the predicted values of $\hat{X}$ of the first step (see equation 4). In doing so, the 2SLS only uses changes in X which are caused by the instrument. Conditioned on assuming the exogeneity of the instrument, this eliminates other related confounding factors as described in subchapter 3.2 (Angrist et al., 1996; Imbens, 2014).

$$\hat{X}_i = \beta_0 + \beta_1 Z_i + \varepsilon_i \tag{3}$$

$$Y_i = \beta_0 + \beta_1 \hat{X}_i + \varepsilon_i \tag{4}$$

However, to investigate the causal effect of education on health by using the C9-reform as an instrument, we have to include additional covariates in the model to control for endogeneity of the instrument in the education-health relationship (Brito and Pearl, 2012), as additional factors may have affected the implementation of the reform, years of education and individuals' health levels (see Figure 16). On the one hand, characteristics of the federal state of schooling or state-specific time trends may have affected the implementation of the reform and introduced differences in the health system. On the other hand, some individual characteristics such as age, gender, cohort membership, and cohort-related age-trends may have affected the reaction to the reform, years of education and health (for detailed information see Chapter 4 and Cygan-Rehm, 2018; Delaruelle et al., 2015; Kemptner et al., 2011; Pischke and Wachter, 2008). Therefore, the following specifications emerge, in which Z_i denotes the assignment to the treatment or the control group based on the reform, $\hat{S}_i$ denotes the predicted years of education and H_i denotes individuals health (behavior):[3]

$$\hat{S}_i = \beta_0 + \beta_1 Z_i + \beta_2 age + \beta_3 age^2 + \sum \left(\mu_{state} + k_{state} * cohort\right) + \sum (\vartheta_{cohort} + \rho_{cohort} * age) + \sum \sigma_{wave} + \varepsilon_i \tag{5}$$

$$H_i = \beta_0 + \beta_1 \hat{S}_i + \beta_2 age + \beta_3 age^2 + \beta_4 sex + \sum \left(\mu_{state} + \delta_{state} * cohort\right) + \sum (\vartheta_{cohort} + \rho_{cohort} * age) + \sum \sigma_{wave} + \varepsilon_i \tag{6}$$

5.5 Investigating mediation effects

Along with the identification of the causal effect of education on health, it is also important to investigate causal mechanisms assumed to be relevant in the relationship. On the one hand, for causal inference, mediation analyses have additional explanatory value regarding the process behind the overall causal effect of a treatment (X) on an outcome (Y). This is because if X is causally linked to a mediator (M) and M is also causally related to Y, M can be seen as one explanation of the effect of X on Y. On the other hand, evidence of a mediation effect between the treatment and the outcome also contributes to the discussion of causality between the two, as such evidence provides further substantiation of the causality of the effect of X on Y (Hedström and Ylikoski, 2010). Therefore, in order to investigate the effect of education on health in middle-aged adults, Article 2 examines the mediation effects of education on mental health through social relationships.

Following the strategy suggested by Baron and Kenny (1986) and VanderWeele (2015), my Co-Author and I do this in several steps. In the main analysis, we first assess the empirical associations between education and mental health with respect to the total effect of education. Second, we add the overall level of social integration, being married or cohabited, the number of close social relationships outside the household, and active membership in voluntary associations as mediators to the equation (each separately). Third, we provide the indirect effect by differentiating the coefficients of education on health predicted in step one and step two. Finally, we tested whether the indirect effects are statistically significant from zero using a test proposed by Sobel (1996). In addition, to complement the random-effects estimation based

[3] To validate the two-stage least squared estimator we run several statistical tests as suggested by Stock and Yogo (2005) and Baum et al. (2007).

analyses in the main part, we were able to conduct fixed-effects regression models on the effect of each social network characteristic for health. Thus, Article 2 not only contributes to the previous literature by addressing questions about causal mechanisms, but also aims to estimate the causal effect of social network characteristics on individual health.

6 Summary and conclusions

The central objective of this dissertation project is to address existing limitations and research gaps revolving around the question of the causal effect of education on health. Specifically, within three studies, the project considers several methodological challenges, addresses theoretically relevant mechanisms, and examines the factor of variation by age. Chapters 2 to 4 present the empirical analyses performed and provide a detailed discussion of their results. In the following and final chapter, I summarize the main findings of my research, as well as its limitations. I also draw some conclusions concerning the questions raised at the outset of this thesis and offer an outlook for future political interventions and empirical research.

6.1 Main findings and limitations

The three empirical studies contribute to ongoing debates about the effect of education on health, the related mechanisms and variations in the effect. They all focus on the causality of the effect by employing different methods that approximate a causal interpretation. One study in particular examines the effect of education's different functions and sheds light on two dimensions linking individuals' education to health in children (Article 1: "*The impact of children's academic competencies and school grades on their life satisfaction: What really matters?"*). The second study investigates the relevance of theoretically expected mechanisms based on to the assumption that education raise individuals' levels of social resources within the working-age population (Article 2: "*The intervening role of social relationships in the effect of education on mental health"*). Finally, a third study concentrates on methodological challenges and revisits the causal effect of education on health in older adults (Article 3: *"Revisiting the Causal Effect of Education on Health").*

In Article 1, this thesis shows the effects of different measurements of education on early mental health outcomes. By investigating differences in individuals' life satisfaction by school grades and academic competencies in a sample of secondary school children with panel fixed-effects regression models, this study highlights that positive changes in school grades, in particular, are associated with higher levels of life satisfaction. In contrast, increases in the academic skills of reading and mathematics appear to be related to individuals' life scores only in some particular cases. Accounting for heterogeneity by school track attended and gender, this study shows that for specific subgroups increasing math competencies cause differences in individuals' life evaluations. For example, children in lower and middle secondary school tracks report lower life satisfaction, the higher their competence level in math. In addition, increasing mathematical competencies lead to higher levels of life satisfaction in girls. In sum, Article 1 reveals that for all children in secondary schools, school grades are highly important for their life satisfaction, but skills and competence levels (here academic competencies) only affect specific subgroups. These findings contradict previous results indicating that academic competencies are generally important for children's life satisfaction (e.g. Bücker et al., 2018; Chen and Lu, 2009; Lyons and Huebner, 2016), while also highlighting the importance of confounding factors in previous studies, which are not controlled for important background factors.

Article 2 complements the results presented in Article 1 by showing deeper insights into the relationship between education and mental health within the working-age population, and the mediation effect through social resources. This study suggests that an individual's hypothetical years of education increase the probability of reporting at least good mental health in adults aged between 30 and 60. In addition, it supports the theoretical argument that social relationships explain some part of the effect. In causal mediation analyses, this article highlights that the individuals' level of overall social integration, the number of close friends and relatives outside the household, and the active membership in a voluntary association all contribute to the effect of education on mental health. In addition, in sensitivity analyses, this article highlights differences in the mediation effect depending on the health outcome investigated. While social relationships seem to explain a substantial part of the education's effect on mental health, they do not offer similar explanatory value regarding the effect of education on individuals' subjective ratings of their overall health status. As a result, this article supports a mediation chain via social resources in the effect of education on mental health, but casts doubt on the relevance of the education's effect on individuals' overall health status. These results are in line with previous studies (Lee, 2011; Marmot et al., 1998; Vonneilich et al., 2012), but contradict theoretical arguments arguing for a mediation in physical and mental health and daily functioning.

Contrasting the result of articles 1 and 2, Article 3 does not support a causal effect of education on individuals' health in older adults. Results of the instrumental variable approach raise concerns about, whether durational changes in compulsory schooling affect individuals' subjective evaluation of their overall health, body mass index, the risk of being overweight or obese, and health behavior. Although the OLS regression results support associations of individuals' actual time spent in school with these respective outcomes, the two-stage least square estimator does not support these associations, except for the effect of education on individuals' alcohol consumption levels. This also holds in several robustness checks and by replicating the results of the forerunner study, which in contrast find causal effects of education on long-term illnesses and working disabilities, physical constitution, and health-related behavior (Kemptner et al., 2011). In sum, this article suggests that education appears to be unrelated to individuals' health in advanced ages; it is thus in line with a large number of studies that find zero effects of education on individuals' subjective evaluations of their overall health status, BMI, and health-related behavior (Hamad et al., 2019; Hamad et al., 2018; Xue et al., 2021).

Therefore, related to the first research question: *"Does education positively affect individuals' health?"*, the conducted empirical studies suggest a variation in the effect of education on individuals' mental and overall health according to actual and hypothetical years of education, academic competencies, school grades, and age groups studied. While, for instance, articles 1 and 2 suggest weak effects of individuals' education levels (i.e. school grades and hypothetical years of education) on self-rated good mental health and life satisfaction, Article 3 indicates that, except for a causal effect on individuals' alcohol consumption levels, the actual length of time spent in general education does not causally relate to individuals' health in older age groups. In addition, it contrasts some of the theoretical arguments highlighted in subchapter 2.4, which suggest stronger effects of education on health in advanced ages. The three studies only partly confirm these expectations since they reveal educational differences in mental and overall health for children and working-age adults, but not for older individuals. Thus, considering methodological challenges, i.e. sophisticated strategies to identify causal effects, variation by age does not reveal a clear answer to the question. In contrast, it is possible that the effect varies depending on the subgroup studied and on the methodological assumptions made.

Regarding the research question: *"Do skills and knowledge levels and the signals of education positively affect individuals' (mental) health, and are these two different facets interrelated?"*, the empirical studies provide evidence for differences in the effect of education on health based on the operationalization of education. Article 1 shows that, for children and adolescents, skills and knowledge levels seem to be less important for mental health outcomes than signals of education. Regression analyses further indicate that the effect of signals of education is unrelated to the skills and knowledge levels of children. Irrespective of actual academic competencies, school grades affect children's life satisfaction. Similarly, Article 2 highlights the relevance of the signals and the symbolic character of education based on the hypothetical years of education in general and vocational schools, which, among other things, represent the highest educational certificates obtained. In contrast, Article 3, which uses individuals' actual time spent in school to examine the effects of education on health, reveals that education does not cause differences in health. Since actual time spent in school is closely related to the argument of skills training, these results cast doubt on the effect of education through higher levels of skills and knowledge. Thus, the empirical analyses of this project suggest that signals of education and the symbolic character of education contribute more strongly to individuals' health outcomes than actually obtained levels of skills and knowledge. These findings, however, contradict theoretical arguments arguing in favor of the relevance of skills and knowledge levels. In addition, they are in conflict with prior literature which generally found no effects of education on health irrespective the operationalization of education used (Xue et al., 2021).

Referring to the research question: *"Do social relationships mediate the effect of education on health?"*, this dissertation project highlights the relevance of strong social relationships for individuals' mental health and overall health status. In mediation analyses, empirical findings suggest that the overall level of social integration and the number of close friends and relatives outside the household partly explain the effect of years of education on individual evaluations of mental health. In addition, sensitivity analyses reveal weak mediation effects of the number of close friends and relatives outside the household for individuals' overall health status. In line with Vonneilich et al. (2012) and Lee (2011), this implicates that social resources in part explain the relationship between education and health, particularly mental health outcomes. However, the results of this study also support previous research that found only weak mediation effects, suggesting a greater relevance of other education-related resources for health (e.g. Ettner and Grzywacz, 2003; Marmot et al., 1998; Vonneilich et al., 2012).

In addition to these three research questions, the three studies also highlight the importance of confounding factors in the effect of education on health. For instance, Article 1 suggests that for children and adolescents the association between academic competence and life satisfaction is driven primarily by important time-constant background factors. In addition, Article 3, despite strong positive associations between education and health, highlights the relevance of confounding factors for individuals' evaluation of their overall health status. Furthermore, Article 2 demonstrates that strong positive associations found in random-effects panel regression models are only partially confirmed in fixed-effects regressions. In particular, the fixed-effects regressions for marital and cohabitation status, and active participation in voluntary associations cast doubt about the relevance of the mediation effect of education on mental and general health by these two indicators. Thus, the consideration of important background factors implies a high importance of selection processes, which is in line with theoretical arguments suggesting a causal relationship between the two, but also proposing that confounding factors underlie the relationship.

The empirical results reported so far, however, should be considered against the background of several limitations. First, although all analyses examined the causal effect of education on health using various methods of modern causal analysis, such as a quasi-experimental design, mediation analyses, and fixed-effects panel regressions, the causal interpretation of the results may remain limited. For example, articles 1 and 2 might be limited due to unobserved heterogeneity. On the one hand, random-effects panel regression models could not account for time-constant individual characteristics and, thus, merely present associations between education and health. On the other hand, fixed-effects regression models may suffer from unobserved time-varying heterogeneity. Thus, although fixed-effects regression allows for a more strongly causal interpretation of effects, it is also subject to limitations in this respect. In addition, Article 3 might be limited because the contrary effects of another reform, namely the introduction of short-school years, could only be partially addressed. Although this study considers class-repetition as one source of endogeneity in analyses, short school years could further bias the results since they might lead to systematic differences in the levels of skills and knowledge acquired during similar lengths of time spent in the educational system, based on individuals' health and confounding factors (Hampf, 2019; Kemptner et al., 2011). Thus, the expected growth of skills and knowledge based on the expansion of compulsory schooling could be smaller than expected for some subgroups. This may result in biased estimates and, therefore, lead to flawed conclusions about education's causal effect on health. Based on these methodological limitations, the interpretation of the causal effects should be viewed with caution.

Second, all results might be limited due to the selectivity in the samples analyzed. Since all studies use panel survey data to address the causal effect of education on health, this limitation could arise from selective panel attrition during the observation period. Based on individuals' characteristics, they exhibit different probabilities of participating in panel surveys. In particular, health and education-based selection restrain the generalizability of the results, because the studies concentrate on the healthier and higher educated part of the population. For example, Article 1 only focuses on children and adolescents, who remained in one school during the observation period, thereby excluding children with discontinuous educational trajectories and school changes from the study. Thus, children with lower skills levels from precarious backgrounds or unstable family constellations are most likely excluded from the analyses, again possibly limiting the empirical results presented in Chapter 2 with respect to their external validity. In addition, since Article 3 focuses on older respondents, the study includes only individuals that are still alive and stayed in the panel until the time of observation (e.g. Dupre, 2008). Similarly, the sample studied in Article 2 likely also suffers from health-based panel attrition. Consequently, both samples consist of a selective part of the population.

6.2 Final conclusion and outlook

Despite its limitations, this thesis provides three general conclusions: first, it highlights that investigating the causal effect of education needs to employ *sophisticated strategies and to address methodological challenges*. Although various studies use valuable strategies for investigating the causal effect of education on health, this thesis demonstrates that improving designs used in prior research may lead to different conclusions. For instance, considering children's academic competence levels and school grades in one study design and using fixed-effects regression models highlights the fact that, contradicting prior research (Bücker et al., 2018), children's school grades affect their life satisfaction more strongly than competencies. In addition, investigating the mediation effect of education on health via the number of social relationships while only considering related indicators in a causal mediation analysis reveals that, in particular, the number of close friends and relatives outside the household and the active participation in a voluntary association may explain some part of education's effect on mental health. Furthermore, replicating prior designs and further developing existing strategies raises concern for an effect of general education on health. This thesis also highlights the value of considering different operationalizations of education and health in one study. Articles 1 and 2 provide empirical evidence of the varying impact of educational signals and skills and knowledge levels, on the one hand, and on variation in the effect of education on mental and overall health on the other. This underlines the importance of distinguishing between the functions of education and the dimensions of health in theoretical explanations and empirical designs. Additionally, it demonstrates the relevance of specifying the concepts investigated. Given the diverging theoretical approaches, it seems plausible that varying functions of education are interrelated with different education-based resources affecting health. Therefore, this thesis highlights the relevance of theory-based empirical research considering methodological challenges to investigate the causal effect of education on health.

Second, this thesis illustrates that examining the causal effect of education also needs to *consider relevant mechanisms*. By investigating the mediation effect of education on health through the number of social relationships, I show that causal explanations may vary depending on the outcome addressed. Thus, although all theories aim to explain differences in health by education in general, empirical results support differences depending on the dimension of health addressed. For instance, while Article 2 highlights an indirect effect of education on mental health via the number of social relationships, it only provides limited support for individuals' evaluation of their overall health status. This signals the importance of investigating the relevant mechanisms in relation to the health outcome addressed. In addition, it illustrates the impact of theory-based empirical research and the need to argue for the specific effects of education based resources on different health outcomes. Thus, this thesis once again underlines the special importance of the investigation of specific mechanisms.

Third, this thesis exemplifies the relevance of considering *heterogeneous effects by age*. For example, it points to the fact that the effect of education on health begins at an early age, and illustrates that educational processes leave traces even in childhood. Receiving poor grades in school appears to affect children's life satisfaction and, thus, may represent an early risk factor for mental distress and illnesses. Furthermore, this thesis shows that education is associated with better mental and overall health evaluations in the working-age population. However, the findings of this thesis do not support a causal effect of education on health in older adults. Compared to the results presented by Kemptner et al. (2011), this contradicts prior results and does not confirm the theoretical arguments. Therefore, it is here indicated that in studying the effects of education on health, age differences should be taken into account to provide a more differentiated answer to the question of whether education affects health.

Along with their three main conclusions, the aforementioned studies also offer several important implications for further research. First, this thesis highlights the need for sophisticated strategies to identify causal effects. Methodological limitations, which affect the existing evidence, need to be further addressed in future investigations. On the one hand, future research should try to test the assumptions made in quasi-experimental designs. Although some studies did this in the last decades, this kind of research is still scarce for different types of exogenous variation used (for example, see Angrist and Pischke, 2009; Cygan-Rehm, 2018;

Hampf, 2019). In addition, replication studies are necessary to support the evidence so far presented. In particular, results of Article 3 indicate that, although they did not lead to different conclusions, each decision made by the researcher affects the results to some extent. It seems highly valuable to examine the strategies used in previous studies in more detail via replication studies to improve the methods developed for the identification of causal effects.

Second, and in close relation to the first, the findings presented suggest further research concerning the differences in the effect of education on health by the function of education addressed and the population studied. On the one hand, future research should focus more strongly on the education's different dimensions in order to obtain deeper insights into their relevance for individuals' health. This is important to help policymakers identify more valuable strategies for reducing the negative consequences of insufficient education. In addition, it may provide a deeper understanding of why educational inequalities in health persist over time even though the average level of educational achievement continues to increase. For example, if the signals and symbolic nature of educational achievement are more important than the skills and knowledge gained through education, health disparities persist because the functions of social closure and social selection based on education continue to operate. Thus, future studies should scrutinize the effect of skills and knowledge levels and educational certificates within one design to understand their individual contributions to differences in health. On the other hand, future research should further address variation by age and other individual characteristics. Since this thesis highlights differences by age and robustness checks in Article1 reveal further heterogeneity by gender, future research should focus more strongly on the differences in the effect of education on health prompted by individual characteristics. It seems that, depending on the population studied, the causal effect of education on health varies substantially. Thus, inconclusive results in prior research could also be due to systematically unconsidered differences by individual characteristics.

Finally, future research should further explore the mechanisms that theoretically link education and health. Although a larger number of studies already provides valuable insights into how education affects health through different types of resources, several research gaps could still be addressed. For instance, the relevance of health-related knowledge and psychological resources is still unclear. In addition, future research should further investigate the contribution of different aspects of a mediation chain for different health indicators, to see whether the same factors contribute to physical and mental health and daily functioning. Lastly, future research should examine the causality of the mediations expected. Since most studies could not account for important background characteristics, empirical findings highlighted in subchapter 4.2 are most likely biased by unobserved confounding factors. Therefore, it is important to expand the research on this topic.

To conclude, although much has been done in the last decades to identify education's causal effect on health, this thesis offers a more diversified understanding of this relationship. As has been illustrated, it is highly valuable to take into consideration the methodological challenges, such as the different operationalizations of education and health, and different subgroups in order to identify education's causal effect on health and to obtain more profound insights into the differences within this effect. In addition, it is important to address causal analyses of mediating effects to understand education's impact on health.

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Appendix

Table A1: Studies Investigating Mediation Effects in the Effect of Education on Health

Author	Year	Title	Education	Health	Mediators	Data	Method	Identification of Mediation
Antonucci et al.	2003	The effect of social relations with children on the education-health link in men and women aged 40 and over	level of education (categorical)	number of health problems	social support	cross-section	not available	not available
Bennett et al.	2009	The contribution of health literacy to disparities in self-rated health status and preventive health behaviors in older adults	holding a high school degree	self-rated fair or poor health status	health literacy	cross-section	probit regression models	Baron & Kenny Approach, Sobel test
Brand et al.	2007	Do job characteristics mediate the relationship between SES and health? Evidence from sibling models	years of education	self-rated health status (global) cardiovascular diseases musculoskeletal health limitations depression	Income, occupational education, physical job characteristics, cognitive job characteristics, job control	longitudinal	structural equation models with sibling fixed effects	Causal mediation Analyses, BIC test for model specification
Ettner & Grzywacz	2003	Socioeconomic status and health among Californians: An examination of multiple pathways	level of education (categorical)	self-rated poor health depressive symptoms	social relationships, health behaviors, financial strain, health care access	cross-section	multiple logistic regression analysis	Changes in coefficients
Friis et al.	2016	Health literacy mediates the relationship between educational attainment and health behavior: A Danish population-based study	level of education (categorical)	risk of being obese	health literacy	cross-section	logistic regression model	KHB Method
Hoffmann & Lutz	2019	The health knowledge mechanism: evidence on the link between education and health lifestyle in the Philippines	years of education	health-behavior (physical activity levels, dietary behavior, medical health care, hand washing and not drinking untreated water)	health-related knowledge	cross-section	propensity score matching logistic regression model	KHB method

Table A1: Studies Investigating Mediation Effects in the Effect of Education on Health (continued)

Author	Year	Title	Education	Health	Mediators	Data	Method	Identification of Mediation
Kenkel	1991	Health behavior, health knowledge, and schooling	years of education	health-behavior (smoking, alcohol consumption, physical activity)	health-related knowledge	cross-section	tobit regression models	Baron and Kenny Approach, McDonald and Molfitt Approach for tobit modells
Lastrucci et al.	2019	Health literacy as a mediator of the relationship between socioeconomic status and health: A cross-sectional study in a population-based sample in Florence	holding a bachelor's or master's degree (binary)	self-rated health status	health literacy	cross-section	logistic regression analyses	Causal mediation Analyses
Lee	2011	Pathways from education to depression	level of education (categorical)	depression	cognitive ability, economic resources, social status, social network, health behavior	cross-section	tobit regression models	Baron and Kenny Approach, changes in coefficients
Lynch	2006	Explaining life course and cohort variation in the relationship between education and health: The role of income	years of education	self-rated health (global)	income	longitudinal	structural equation modeling	Baron and Kenny Approach, product method , two tailed t-tests
Milner et al.	2018	Do employment factors reduce the effect of low education on mental health? A causal mediation analysis using a national panel study	not completing high school	mental health inventory	occupation skill level, labor force status	longitudinal	structural equation model	Causal mediation Analyses

Table A1: Studies Investigating Mediation Effects in the Effect of Education on Health (continued)

Author	Year	Title	Education	Health	Mediators	Data	Method	Identification of Mediation
Murrell, Salsman & Meeks	2004	Positive and negative psychological states and economic status as mediators of the relationship of education to fatigue among older adults	years of education	fatigue somatic symptoms dysfunction pain	income housing quality sadness obsessivness calmless well-being	longitudinal	regression analysis (function unknown)	Baron and Kenny Approach, t-test for changes in coefficients
Schillinger et al.	2006	Does literacy mediate the relationship between education and health outcomes? A study of a low-income population with Diabetes	level of education (categorical)	diabetes	health literacy	cross-section	structural equation model	chi-square difference test for model comparison
Sheikh et al.	2017	Education and health & well-being: Direct and indirect effects with multiple mediators and interactions with multiple imputed data in Stata	level of education (categorical)	health-related quality of life (EQ-5D)	income management position occupational hierarchy position	longitudinal	Poisson regression models	Causal mediation analysis, Inverse Odds Weighting approach,
van der Heide et al.	2013	The relationship between health, education, and health literacy: Results from the Dutch adult literacy and life skills survey	level of education (categorical)	self-rated health status (global) self-rated mental health status self-rated physical health status	health literacy	cross-section	linear regression models	Baron & Kenny Approach, test proposed by MacKinnon et al. (2002)

Chapter 2 – The impact of children's academic competencies and school grades on their life satisfaction: What really matters? (Article 1)

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[4] Including some small corrections compared to the published article.

Abstract

Increasing demands in schools, higher pressure on children's performance levels, and increasing mental health constraints raise questions about the impact of educational achievement on children's life satisfaction. Therefore, this study investigates whether children's academic competence levels and school grades affect their life satisfaction and if the effects vary by educational track. Complementing prior research, this study firstly uses fixed-effects regressions to get closer to the estimation of the causal link between children's academic competencies, school grades, and life satisfaction by eliminating time-constant confounding factors such as intelligence, early background characteristics, and genetic factors. By using valuable longitudinal data on academic competencies, school grades, and life satisfaction of children from a sample of 5th-grade students (N=3,045) of the National Educational Panel Study in Germany (NEPS) from 2010 to 2015 this study reaches also a broader external validity than prior research. Including various tracks makes testing for heterogeneous effects by school track attended possible. Results indicate that, on average, children's school grades seem to be highly important for their life evaluations. Moreover, the effect of school grades does not vary across educational tracks, i.e. school grades seem to matter for all children. In contrast, levels of academic competencies seem to be relevant only for specific subgroups. Investigating effect heterogeneities reveals that only among children in the lower secondary school tracks higher competencies are related to lower life satisfaction. Overall, the study highlights the importance of school grades and point out variation in the relevance of competence levels between school tracks.

1 Introduction

High levels of mental health problems around the world are one of the most serious challenges in modern societies and about 50 percent of mental health problems in adulthood can be attributed to childhood and early adolescence (World Health Organization, 2018, 2019). Especially lower levels of life satisfaction and feelings of unhappiness in childhood are associated with a higher risk of later life mental illness (Gilman and Huebner, 2003; Park, 2004). Thus, an increasing number of studies investigate early inequalities in children's life satisfaction and ask for valuable strategies for enhancing their emotional well-being to prevent longstanding inequalities in individual mental health (Gilman and Huebner, 2003). As a result, various strategies for increasing individual life satisfaction are discussed, with early investments in education often seen as the most favorable ones (for review see Powdthavee et al., 2015).

For children, schooling coincides with periods of emotional upheavals, biological and neurobiological changes, as well as social development. Increasing levels of school-related stressors are assumed to interfere with developmental changes and the increasing demands on children's educational achievement and higher pressure in schools result in lower levels of children's life satisfaction and a higher number of mental health constraints (Gilman and Huebner, 2003; Hascher et al., 2018).

Thus, investigating the effect of children's educational achievement on their life satisfaction might help to address early inequalities in their well-being and mental health outcomes. To investigate the effect of early educational achievement on life satisfaction in children, empirical studies mainly focus on academic competencies and school grades (e.g. Chen and Lu, 2009; Edgar et al., 2015; González et al., 2020; Lyons and Huebner, 2016; Rathmann et al., 2018; Suldo et al., 2008). Both concepts indicate one's performance in school, are related to predefined goals within educational settings and directly refer to the whole process of schooling (Smith 1995). However, although students' actual academic competence levels and school grades are part of the same construct, they often show differences because they include different aspects of achievement evaluations. On the one hand, children's competence levels refer to the actual level of skills and knowledge acquired in education. They indicate how much children have learned in a given subject (Willingham et al., 2002). On the other hand, school grades rather reflect teachers' evaluations of the performance level of children in school. They serve as a signal of recognition of achievement and, although they reflect differences in competence levels, they usually include an assessment of children's behavior in and outside the classroom, their perceived motivation, and individual as well as background characteristics (Lekholm and Cliffordson, 2008; Willingham et al., 2002). Thus, children's levels of academic competence should affect their school grades, but grades do not automatically represent differences in children's competencies since grades also depend on children's behavior and learning motivation (Steinmayr and Meißner, 2013).

Differences in the effect on life satisfaction could result from differences in the perceived relevance of school-related competence levels and school grades for educational success. Whereas the actual levels of academic competencies are rather unknown for children, school grades are important indicators for performance levels. School grades directly represent feedback on children's school performance and convey the increasing performance expectations placed on children. Getting bad grades could implicitly signal failure in school and create fears about one's future opportunities. Thus, school grades might be of higher relevance in children's' life evaluation because better grades are perceived as important indicators for their success in education. Moreover, there might be theoretical guided interdependencies between both which have not yet been considered.

In empirical research, results regarding the associations between academic competencies, school grades, and children's life satisfaction are mixed. Depending on the cultural context, age group studied, and the level of education, studies show positive and negative associations as well as the lack of correlations. For instance, students' academic competencies are positively associated with general happiness among 11th graders in Taiwan (Chen and Lu, 2009), with global life satisfaction in seventh and eighth graders in middle schools in the southeastern United States (Lyons and Huebner, 2016), and with higher life satisfaction among 10- to 19-year-old children in boarding schools in Australia (Martin et al., 2014). In contrast, Bradley and Corwyn (2004) find negative associations in a sample of 10- to 15-year-old children in a small county in the United States. For children's school grades, González et al. (2020) highlight that higher previous-year grade point averages are linked to higher life satisfaction among 13-year-old children in Chile. Additionally, Edgar et al. (2015), Rathmann et al. (2018), Reysen et al. (2017), and Ng et al. (2015) show that better grades are related to higher levels of life satisfaction of children in different age groups in New Zealand, Germany, and the United States. In contrast, MacCann et al. (2012) did not find any statistically significant association in the U.S.

Although the existing studies provide important and interesting insights into this research topic, some limitations will be addressed in this study.

First, given that results on academic competencies and school grades stem from different studies or different regression models, it is difficult to compare the effects of children's academic competencies and school grades on life satisfaction. While these studies provide interesting insights into either the effects of competence levels or school grades, there is still a need for a study design that provides for both estimating and comparing the effects of competencies and school grades in a joint study.

Second, previous research is mostly based on cross-sectional designs or employ structural equation models based on panel data, which render it difficult to conclude the causality of the relationship between children's academic competence levels and school grades and their life satisfaction (e.g. Chen and Lu, 2009; Gilman and Huebner, 2006; MacCann et al., 2012; Martin et al., 2014; Ng et al., 2015; Reysen et al., 2017; Suldo et al., 2008). Identification in these studies is based on the strict assumption of selection on observed factors. Hence, biases may occur if there are unobserved confounding variables such as intelligence, early background characteristics, and genetic factors, which may occur due to data limitations. In contrast, a longitudinal study with repeated measures of academic competencies, school grades, and life satisfaction and using fixed-effects regressions would allow eliminating time-constant unobserved confounding variables (Brüderl and Ludwig, 2015). This offers better opportunities to make estimates that are closer to the true causal effect. However, it must be emphasized that also fixed-effects regressions can still be biased if there are unobserved time-varying confounding variables.

Third, previous studies are mainly based on specific subgroups that generate a high variation in estimation results about the relationship between education and life satisfaction based on sample characteristics. For example, there are studies on special samples such as university students (e.g. Grunschel et al., 2016; Schmitt et al., 2008), higher secondary school students (e.g. Edgar et al., 2015; Reysen et al., 2017; Suldo et al., 2008), students in only small districts (e.g. Bradley and Corwyn, 2004) or special schools and programs (e.g. Martin et al., 2014). These sample differences can be one explanation for the variation in findings across studies. A limitation of these subgroup-specific studies is that no general conclusion about the link between children's academic competence levels, school grades and life satisfaction can be drawn, and comparisons between subgroups are not possible.

Against this background, I investigate the effect of children's academic competence levels and school grades on life satisfaction. The present paper tries to fill the research gaps in the existing literature described above in several ways. First, instead of just focusing on either academic competencies or school grades this study analyzes the effects of both as well as differentiate between competence levels in reading and math. This allows for a comparison of the effects of academic competencies and grades on life satisfaction in one study design. Second, the study addresses data limitations of previous research by deploying prospective panel data from the German National Educational Panel Study (NEPS) on educational trajectories of students in secondary school. The NEPS includes reliable repeated measures of children's skill levels through validated standardized tests, which identify core components of competencies and allow linkage between test scores across panel waves (Weinert et al. 2011), school grades, life satisfaction, and other background characteristics. To get closer to the true causal effect than previous studies, this study uses the advantages of the panel data by deploying fixed-effects regression models to eliminate time-constant unobserved confounding variables. Finally, regarding the issue of external validity, this study includes students from various secondary school tracks and not only selective subgroups. This contributes to the scarce literature investigating broad samples and heterogeneity in the effect of children's competence levels and grades on their life satisfaction (e.g. Nordlander and Stensöta, 2014). Thus, I test for effect heterogeneity, i.e. to investigate whether the effects of competencies and grades on life satisfaction differ between the school tracks attended.

2 Theoretical considerations and hypotheses

2.1 The effect of children's competence levels and school grades on life satisfaction

To answer the question of how children's levels in academic competencies and school grades affect their life satisfaction the literature provides various theories, which consider economic and psychological approaches and stress different theoretical mechanisms. In the following, I focus on arguments of the human capital theory but complement the theoretical arguments with explanations of the psychological theory of self-determination to consider also psychological processes (Grossman, 2006; Ryan and Deci, 2000).

From both perspectives, children's levels of academic competence should enhance their life satisfaction, because they are assumed to represent *individuals' skills and knowledge levels acquired in education*. Higher levels of skills and knowledge are assumed to enhance children's life satisfaction, firstly, because they increase children's abilities to manage highly demanding tasks and being able to adapt to changing external or internal demands resulting in better coping with stressful life events (Grossman, 2006; Smith and Carlson, 1997). This prevents emotional or behavioral problems and, thus, avoids negative consequences on children's life satisfaction caused by external stressors (Smith and Carlson, 1997). Secondly, higher skills and knowledge enhance children's life satisfaction, because they foster children's abilities to use given resources, e.g. pocket money, more efficiently (Grossman, 2006). This allows higher quality and quantity of investments in relevant means producing life satisfaction, like going to the cinema, buying treats, or important clothes and toys. Thirdly, higher skills and knowledge levels enable children to choose positive input and avoid the negative to enhance their life satisfaction levels (Grossman, 2006). Thus, children with higher skills and knowledge levels tend to avoid early health-damaging behavior, like smoking and excessive alcohol consumption, participate more often in positive activities, like doing sports, instead of being delinquent, or might choose better friends, who provide emotional or school-related support. Positive health behavior, participation in beneficial leisure time activities, and higher levels of social support, in turn, are associated with higher levels of life satisfaction (e.g. Hu and Mu, 2020; Moore et al., 2018; Proctor et al., 2009). Finally, higher levels of skills and knowledge increase the individual's life satisfaction levels by satisfying one of the three innate psychological needs, namely the need for competence. Next to the need for relatedness and the need for autonomy, feeling competent is assumed essential for an individual's psychological well-being. It is assumed that higher levels of skills and knowledge increase children's life satisfaction as they reinforce their feelings of competence by experiencing high effectiveness in mastering daily challenges and given tasks (Ryan and Deci, 2000).

Therefore, I derive my first hypothesis:

H1: The higher the children's levels of academic competencies, the higher their life satisfaction.

Regarding the effect of children's school grades, however, psychological approaches highlight the importance of positive or negative evaluations of children's performance in and outside school. During childhood, individuals create their self-image based on the feedback of others and opinions about themselves in daily life. Thus, independently of the true level of skills and knowledge, children develop perceptions of their (in-)competence depending on the feedback received. Next to feedback from parents and peers, especially the feedback from teachers in terms of school grades is expected to play a central role. Therefore, positive evaluations in the form of higher grades are assumed to increase children's perceptions of competence and should increase children's levels of self-esteem, self-perceived efficacy, and future optimism, which are closely linked to higher levels of life satisfaction. In contrast, negative feedback in terms of low school grades should result in lower levels of life satisfaction, because children attribute the negative evaluations to their skills and knowledge, develop a feeling of incompetence, and have lower levels of self-esteem, self-perceived efficacy, and future optimism (Cole et al., 2001; Dweck and Leggett, 1988; Eicher et al., 2014; Herman et al., 2008). Based on these theoretical arguments, I derive my second hypothesis:

H2: The better the children's school grades, the higher their life satisfaction.

These hypotheses refer to the unconditioned versions, i.e. the total causal effect of either academic competencies or school grades without controlling for the other. However, other theoretical expectations can be derived for the case when both competencies and grades enter the model simultaneously. In line with the skill-related arguments, the effect of school grades should diminish if academic competence levels are taken into account because they represent direct measures of the unobserved skills. However, since school grades represent more than just differences in skills and knowledge, they may also be of further relevance to children's life assessment, because they refer to positive or negative evaluations of children's performance. Thus, complementing the human-capital approach self-determination theory assumes, that, despite children's actual levels of academic competence, children with lower grade levels should report lower levels of life satisfaction, because getting bad grades might be a signal for failure in a specific task. This results in lower self-esteem, less positive perceptions about one's future, and negative self-evaluations, which might decrease student's life satisfaction (Herman et al., 2008). In contrast, earning higher grades reflect higher goal achievement in school and should lead to stronger beliefs of being competent, higher self-esteem, and higher feelings of self-efficacy, all leading to more positive life evaluations. Therefore, even when competencies are controlled, school grades should positively affect children's life satisfaction. Moreover, school grades might partly explain the effect of children's academic competence levels on their life satisfaction as they refer to the psychological mechanisms. Thus, controlling for grades in the effect of competencies on life satisfaction should result in the estimation of the direct effect of skills on life satisfaction.

This leads to two more hypotheses:

H3: It is expected that the conditional effect of children's levels of academic competencies is lower than the unconditional effect because the effect is partly explained by children's school grades.

H4: The effect of school grades should be smaller in the conditional model compared to the unconditional one because competence levels act as a confounder.

While the theoretical arguments provided so far postulate positive effects of children's competence levels and school grades on life satisfaction, there also exist theoretical counter-arguments as well as implications for a reverse causal link. On the one hand, high levels of competencies and school grades might result in lower levels of life satisfaction if the need for relatedness is not met (Ryan and Deci, 2000). Perceived social exclusion due to rejection or victimization by peers based on high levels of competence and school grades might decrease children's life satisfaction, because, depending on the educational context, extremely high levels of competencies and grades might lead to lower levels of social connectedness. Especially in contexts with lower average levels of skills and knowledge, high-achieving children might have higher difficulties because peers with average skill levels tend to react to the threat of feeling less competent. For instance, they tend to be aggressive or harassing in social interactions with high-achieving children, which might result in lower life satisfaction levels of the affected child (Arslan, 2018). On the other hand, life satisfaction might also enhance children's levels of competencies and school grades, because higher life satisfaction is assumed to increase positive emotions which affect cognitive function and personal resources for learning and acquiring knowledge (Fredrickson, 2004). Therefore, being satisfied with life and having a high value of subjective well-being may enhance individuals' academic achievement (Pekrun et al., 2006; Valiente et al., 2012).

However, even though theoretical arguments suggest negative consequences of children's competence levels and school grades as well as a reverse relationship, these counter-arguments should not negate the previous argumentation. As exemplarily shown by Bergold et al. (2020), higher competence levels prevent children from being bullied in school. Results indicate, that the higher the children's competence levels the lower the prevalence of bullying (Bergold et al., 2020). Therefore, children with higher levels of competence should be less likely to feel socially excluded and diverging effects should not contradict prior arguments. Moreover, as pointed out by Ng et al. (2015), the effect of life satisfaction on school grades seems to be less important compared to the influence of school grades on satisfaction. Thus, even if the effects of children's competence levels and school grades on life satisfaction could be opposite and children's life satisfaction influences their levels of competencies and school grades, the effects postulated in hypotheses one to four should be the dominant ones.

2.2 Heterogeneous effects of children's competencies and school grades by secondary school track

Despite the aforementioned theoretical arguments and the suggested link between children's competence levels, grades, and life satisfaction, it is questionable if the relationship shows up to be similar for all children. As empirical literature suggests, there might be differences between subgroups by several individual-specific or context-related characteristics. Studies indicate differences in the relationship between competencies and school grades and life satisfaction by gender, age, culture, and educational setting (e.g. Chang et al., 2016; Nordlander and Stensöta, 2014; Suldo et al., 2016).

As one important factor of educational settings, school tracks might be of relevance for the effect of children's academic competencies and school grades on life satisfaction. For example, in Germany, the case studied, after primary schooling starting in the age around 6 tracking into lower, intermediate and higher secondary schools occurs at about age ten and this then defines different pathways to further education and training (for detailed information see Figure A1 in the Appendix and Kultusministerkonferenz, 2019). While lower and intermediate secondary schools prepare for vocational apprenticeship training, the higher secondary school track aims to prepare children for tertiary education. Thus, children in different school tracks face different opportunities and constraints for their future. While children in the higher secondary school track face positive prospects in getting a position in vocational training or going on with tertiary education, children in lower and intermediate school tracks are limited to vocational education and face several challenges in getting an apprenticeship. In addition, attending the lowest educational school track does not only affect the number of options for further education and training, it decreases the children's probability of getting a vocational training position tremendously (e.g. Fitzenberger et al., 2015).

These differences in prospects might result in differences in the relevance of school-related feelings of competence for children's life evaluation. It is assumed that, during secondary schooling, children tend to adapt to their perceptions of the future and if necessary compensate for need frustration with alternative strategies. Especially children in the lowest educational school track, who have the lowest level of future opportunities, tend to react to their less prospective future (Eccles and Roeser, 2011). Thus, they are more likely to show maladjustments in terms of ill-being, develop different behavioral patterns stabilizing their self-worth, like heavy gaming, or react to it by oppositional defiance in form of deviant behavior and action against authorities (Vansteenkiste et al., 2020). These adaption processes result in higher relevance of other life domains and therefore shape how children evaluate overall life satisfaction. For instance, these children might be more likely to evaluate their lives in terms of sports, peer relationships, family, and standards of living. In contrast, children in higher secondary schools experience a higher value of school-related feelings of competence based on valuable future opportunities. The possibility of reaching a high level of education could lead to a stronger focus on high levels of school performance because performing well increases their chances to reach the goal. Thus, they pay more attention to school-related feedback and, consequently, children in the higher track should be more affected by a negative response. Since they face a higher risk of losing chances of reaching a higher level of education or prestigious job positions, school-related aspects might be highly important for their life satisfaction.

Therefore, it might well be argued, that the effect of school grades on life satisfaction might be stronger for children in higher secondary school tracks compared to children attending the lower school track. Children in the higher track should be more affected by school grades because they reflect the evaluations of school-related competence levels by teachers and indicate success or failure in terms of school-related tasks. Thus, getting poor school grades might indicate a failure in a specific task, which is accompanied by a higher risk of losing chances of reaching the next level. In contrast, the level of life satisfaction of children in the lowest school track might not vary by school grades, because school-related aspects are not highly relevant in their life evaluations.

However, the link between children's competence levels and life satisfaction might not be moderated by the school track, because the differences between school tracks mainly account for variation in the importance of school-related feelings of competence. Despite that, having higher levels of competence should steadily lead to higher life satisfaction by increasing children's and youth skills in problem-solving and mastering challenges. Irrespectively of the school track attended, children with higher competence levels should have higher levels of coping strategies, manage (school-related) tasks more easily and invest more in positive means to enhance their overall life satisfaction. Therefore, a moderation effect of the school track attended should only be observable for school grades not for children's competence levels.

In line with these arguments, I derive two additional hypotheses:

H5a: The positive effect of children's competencies on overall life satisfaction does not differ between lower, middle, or higher secondary school tracks

H5b: The relationship between children's and youth school grades is weaker in lower secondary school tracks compared to middle and higher secondary school tracks.

3 Methods

3.1 Data

This study uses data of starting cohort 3 (5^{th} graders) of the NEPS in Germany, which is the first to allow for longitudinal analysis of the effect of competence levels and school grades on life satisfaction in children based on representative data in Germany (Blossfeld and Roßbach, 2019). The sample of starting cohort 3 consists of representatively selected 5^{th}-grade students in secondary school tracks in regular as well as special schools. The sample is stratified in class-school levels in the federal states in Germany and contains three subsamples, the main sample including children randomly selected from classes, a migrant supplement including only children with a migrant background, and a refreshment sample in wave 3 (Steinhauer and Zinn, 2016). The annual survey was first conducted in 2010 and paper-based questionnaires and competence tests were administered in classes in schools during one or two school days. However, if a student left school or the school refused further cooperation with the survey institute, questionnaires were sent home. Context information about the school and class level as well as competencies are no longer available for this group.

For the present study, I have used data of grades five, seven, and nine including waves one, three, five, and six, because competencies in reading and mathematics are only available in these respective years. I have only used data of the main sample because the sampling procedure and measurements of children's competence levels differed slightly between the migrant supplement and the main part of the sample (Steinhauer and Zinn, 2016). I have restricted the sample to children who attended at least two waves and use only individuals, who were surveyed in the school context in regular schools. Moreover, I restrict the sample to individuals, which attended the same school during the observation period to ensure a comparable sample structure over time. Finally, I have only included children without missing values in relevant variables, which resulted in 2,602 dropped observations and 488 missed complete cases in total. In the end, the sample consists of 3,045 individuals nested in 155 schools and 356 classes in a maximum of three waves. Each individual was observed about 2.3 times on average. The mean age is about 12 years and ranges from 10 to 15 between waves. About seven percent of the sample attended the lower secondary school track, while about 29 percent and 65 percent attended the middle secondary or higher secondary school track, respectively. Children in the lower secondary school track participated in about 2 waves on average, while children in middle and higher secondary schools participated in about 2.3 and 2.5 waves, respectively.

3.2 Statistical analyses

To test the theoretically-driven hypotheses, I have used fixed-effects panel regression models, which are based on the following basic linear regression model:

$$y_{it} = X_{it}\beta + \alpha_i + \varepsilon_{it} \tag{1}$$

In general, this model refer to a linear relationship between a dependent variable (y_{it}) and two or more independent variables ($X_{it}\beta$) repeatedly measured in subjects (i) and time (t). They have two error components, one representing time-constant subject-specific characteristics (α_i) and an idiosyncratic error term (ε_{it}), which refers to time-varying subject-specific characteristics. By demeaning the variance of subject-specific means, fixed-effects panel regression models use the within variation within subjects over time only to predict the effect of changes in $X_{it}\beta$ on the respective outcome variable (y). This eliminates time-constant subject-specific variation as represented in α_i. Thus, estimates are not biased by time-constant subject-specific confounding factors, like intelligence, family background characteristics, or genes (Brüderl and Ludwig, 2015). However, a bias may occur in case of time-varying confounding variables.

Following the basic idea, for this study the overall regression model is as follows:

$$satis_{it} = \beta_{0t} + \beta_1 competencies_{\,it} + \beta_2\ school\ grades_{it} + \gamma_1 controls + \alpha_i + \varepsilon_{it} \tag{2}$$

Here, $satis_{it}$ denotes children's (i) overall life satisfaction reported on time t and will be explained by children's $competencies_{it}$ and $school\ grades_{it}$. Observed time-varying confounding variables are included as control variables. α_i reflects the time-constant error term including time-constant characteristics, like children's gender, migration background, socio-economic background, personality traits, intelligence, and school context variables. In turn, ε_{it} represents the unobserved time-varying individual characteristics.

The estimation procedure follows a stepwise approach. In the first step, to test hypotheses one and two, the effects of children's $competencies$ (Model 1a) and $school\ grades$ (Model 2a) will be estimated separately. In a second step, to test hypotheses three and four, both indicators will be included in one model (Model 3a). In a third step, following the same procedure from step one and two, interaction effects by school track are included to test the theoretical expectations about heterogeneous effects of the school track attended (Model 1b to Model 3b).

Finally, I conduct a sensitivity analysis for the main effect of children's competence levels and school grades on their life satisfaction by investigating differences in the relationship by gender, since prior literature suggest variation between girls and boys (e.g. Pomerantz et al., 2002; Nordlander and Stensöta, 2014).

3.3 Variables

Life satisfaction Children's *life satisfaction* refers to their overall evaluation of life in terms of goals achievement and subjective criteria in all subjectively important life domains and relates to the cognitive well-being of children (Diener et al., 2009; Diener, 1984; Huebner, 2004). It is linked to individuals' life circumstances, indicates long-term average mood and longstanding consequences of life events (e.g. Diener et al., 2013; Suldo et al., 2016), and is strongly associated with children's mental health (e.g. Fergusson et al., 2015; Gilman and Huebner, 2003). Higher levels of life satisfaction arise if goals are reached and subjective standards in life are fulfilled (Diener, 1984). To measure life satisfaction, I use a single-item question asking "How satisfied are you currently and in general terms with your life?", which is well established in well-being research and shows high reliability compared to multi-item scales, even for youth (Cheung and Lucas, 2014; Frey and Stutzer, 2002; Jovanović, 2016; Kahneman and Krueger, 2006). The scale ranges from 0"completely dissatisfied" to 10 "completely satisfied".[5] For later analysis, the measurement is included as a metric variable. On average, children reported a high level of life satisfaction. I observe a mean level of overall satisfaction of about 8 scale points (see Table 2).

School grade To measure the children's *school grades,* I used the combined mean of students' self-reports of final grade point averages in Math and German of the previous school year ranging from 1 "very good" to 6 "unsatisfactory". Self-reported GPA in German and Math are highly correlated with actual school grades and should be a good substitute for actual GPA (Sticca et al., 2017). Although validation studies indicate, that self-reported school grades are somewhat biased by children's actual school performance levels (Credé and Kuncel, 2013; Kuncel et al., 2005), estimating the effect of school grades on life satisfaction should not be limited by these differences. Since the panel regression model only uses intra-individual variation for predicting the effect of school-grades on life satisfaction time–constant variation between individuals should not bias estimation results. In line with previous research and for easier interpretation, I inverted the scale so that it now ranges from 1 "unsatisfactory" to 6 "very

[5] The published version stated that the scale ranged from 0 to 11, this was however a typing error.

good". Children's school grades range from 1 to 6 and are about 4.6 for German and about 4.5 for Math. Differences between individuals are about 0.7 and 0.8, respectively (see Table 2).

Academic Competencies To measure children's *academic competencies*, I used results of competence tests administered in the domains of reading and math conducted in NEPS, which both represent multidimensional skills of individuals related to these domains (for more details see Weinert et al. 2011). Both tests include a maximum of 33 items and last approximately 30 minutes. Test results are scaled as conditional probabilities for achieving a specific ability level based on Rasch-models and linked by mean-to-mean based on anchor items across waves (Fischer et al. 2016). To analyze the relationship between children's competencies and life satisfaction, I used uncorrected weighted maximum likelihood estimates as recommended by van de Ham et al. (2018) and Scharl et al. (2017). I included the metric scores ranging from -4.39 to 6.82. Sample specific descriptive statistics are presented in Table 2. Children in starting cohort 3 showed lower levels in reading compared to math. While the mean level in reading is about 0.9, the level in math is about 1.1.[6]

School track attended To identify the *school track attended* I used information about the type of school offered in NEPS. I assigned children to the respective secondary school track if they either reported that they attend the respective school type, or the respective level in a comprehensive school or a school with several course levels (see Table 1).

Table 1: Classification of School Tracks Based on School Type Attended

Lower secondary	Hauptschule
	Comprehensive school – lower secondary level
	School with several course levels – lower secondary level
Middle secondary	Realschule
	Comprehensive school – middle secondary level
	School with several course levels – middle secondary level
Higher secondary	Gymnasium
	Comprehensive school – higher secondary level
	School with several course levels – higher secondary level

Source: Own illustration

[6] I estimated additional panel models to check the correlations between individuals' academic competencies and school grades. Results show, that academic competencies and school grades are only moderately correlated. Lower levels in academic competencies are associated with lower grade point averages. However, explained variation for differences between individuals is about 40 percent for GPA in German and GPA in Math. About 30 percent of the variation of school grades are explained by changes in academic competence levels within individuals (for detailed information see Table A1 and Table A2 of the Appendix).

Table 2: Descriptive Statistics of Main Variables (N=7,085; n=3,045)

Variable		Mean	Std. Dev.	Min	Max
Life satisfaction	overall	7.90	2.15	0	10
	between		1.73	0	10
	within		1.40	1.23	14.57
School grade (German)	overall	4.56	0.84	1	6
	between		0.72	2	6
	within		0.49	2.23	6.89
School grade (math)	overall	4.53	0.96	1	6
	between		0.79	1	6
	within		0.58	2.20	7.20
School grade (mean)	overall	4.55	0.78	1	6
	between		0.66	1.50	6
	within		0.46	2.21	7.05
Reading competence	overall	0.91	1.30	-3.41	6.24
	between		1.12	-3.09	5.18
	within		0.73	-2.59	4.26
Mathematical competence	overall	1.05	1.29	-4.57	6.82
	between		1.12	-3.68	4.57
	within		0.73	-2.68	4.48
Age	overall	12.33	1.63	8	16
	between		0.98	9	16
	within		1.40	9.66	14.99
Subjective health status	overall	1.73	0.76	1	5
	between		0.63	1	4.50
	within		0.46	-0.27	4.40

Source: NEPS SUF SC3 9.0.0 (download); doi:10.5157/NEPS:SC3:9.0.0; own calculation

Confounding factors and control variables As discussed in the literature the relationship between educational achievement and life satisfaction might be confounded by several individual and background-related variables. However, since fixed effects regression models already eliminate time-constant confounding variables, I only focused on time-varying components, which are assumed to affect educational achievement and life satisfaction as well as are not already considered by the sample definition and the statistical approach. I control for *children's age, age-wave effects, class-level characteristics,* and *children's health status*. Children's age was included as a metric variable measuring children's age at the time of the interview and class-level characteristics were controlled by considering class-level fixed effects. Children's health status was measured by the question "How would you generally describe your state of health?" with a scale ranging from 1 "very good" to 5 "very bad".[7] Next to these included controls, life events, such as changes in residence, school, or family structure and parental job loss which require high levels of coping and adaption, might also affect children's educational achievement and life evaluation (e.g. Carlson and Corcoran, 2001; Mostafa et al., 2018; Pribesh and Downey, 1999; Proctor et al., 2009). However, due to the

[7] Although objective measurements of children's health status are largely preferred because subjective health status may be biased due to social and psychological factors that influence children's self-monitoring, the NEPS study only provides sufficient information on children's health based on their own subjective ratings.

restriction of the sample only to children without any school change, I observed no changes in residence and school. Moreover, I observed only a very small variation in family structure between panel waves. Thus, residential-, school-and family-related characteristics can be assumed to be time-constant and will be eliminated by the time-constant error term.

4 Results

Results of fixed-effects regression analyses are presented in Table 3 and Table 4. Table 3 shows the results of the estimation of the effect of both measurements of educational achievement on life satisfaction without considering differences by attended school track. The first and the second model show results of predicted life satisfaction on competencies and school grades separately. The third model includes both. For all models, the within-R^2 indicates that the model explains about 13% of the variation in life satisfaction of each individual. For children's competence levels, Model 1a indicates that neither reading nor math competence levels affect children's life satisfaction. Both coefficients are very small and not statistically significantly different from zero. This contradicts hypothesis 1, where a positive effect of children's competencies on life satisfaction was expected. Regarding the effect of children's school grades, Model 2a predicts that an increase by one grade increases children's life satisfaction by about 0.24 scale points, which is in line with the second hypothesis. Model 3a substantiates these results. Children's competence levels seem to be unrelated to their life satisfaction and controlling for school grades, results do not differ between Model 3a and Model 1a. Furthermore, Model 3a shows that school grades are already important for children's life satisfaction even when competencies are controlled. However, contradictory to hypothesis 4, controlling for children's competence levels does not decrease the estimated effect of children's school grades on their life satisfaction.

Regarding hypotheses 5a and 5b, Table 4 shows the results by taking the interaction effects with the school track attended into account. Compared to models 1a to 3a, the main effects of children's grades and competencies now represent the effect of both on life satisfaction only for children in middle secondary school track as they are defined as the reference category in the interactions. Model 1b shows the results of the predicted life satisfaction based on children's competencies. Similar to the main model, children's reading competence seems to not affect their life satisfaction; the coefficient is very close to zero. Nevertheless, considering differences in school tracks change results regarding the impact of mathematical competence on children's life satisfaction. The main effect becomes significantly different from zero and negative, which indicates that children attending the middle secondary school track report lower life satisfaction levels if they achieve higher levels in mathematical competence. This seems to be also true for children in lower secondary schools because observed differences are not significant for this group. In contrast, for children in higher secondary schools, mathematical competence levels appear to be positively related to children's life evaluations, and differences compared to children in middle secondary schools are significant. Model 3b confirm these results, which, however, contradict Hypothesis 5a, because they highlight variation in the effect of children's competence levels on life satisfaction.

Table 3: Results of Fixed-Effects Panel Regression of the Effect of Children's Competencies and School Grades on Life Satisfaction

	Modell 1a	Modell 2a	Modell 3a
Reading competence	0.072*		0.068
	(0.0426)		(0.0426)
Mathematical competence	-0.016		-0.027
	(0.0513)		(0.0507)
School grade (mean)		0.245***	0.244***
		(0.0631)	(0.0632)
Constant	12.640***	10.825***	10.825***
	(0.9710)	(1.0589)	(1.0584)
Within-R^2	0.1318	0.1352	0.1360
Observations	7,085	7,085	7,085
N	3,045	3,045	3,045

Source: NEPS SUF SC3 9.0.0 (download); doi:10.5157/NEPS:SC3:9.0.0
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors by school level in parentheses; controls: age; age-wave effects; class fixed effects; subjective health status, full regression models are presented in Table A3 in the Appendix.

Referring to hypotheses 5b, Model 2b and Model 3b indicate that school grades are still important for children's life evaluations in middle secondary schools and there are no significant differences between school tracks. Although coefficients of the interaction terms indicate that the effect of school grades on the life satisfaction of children who attend the lowest secondary school track is lower than for children in middle and higher secondary schools, these differences are not significant. Moreover, results highlight, that children in higher secondary school track do not differ substantially from children in middle secondary schools since the interaction effect is very close to zero. Therefore, even though the coefficients point in the expected directions, results contradict theoretical assumptions, since these differences are not significant.

Table 4: Results of Fixed-Effects Regressions Including Heterogeneous Effects by School Track

	Model 1b	Model 2b	Model 3b
Reading competence	0.009		0.010
	(0.0895)		(0.0899)
Mathematical competence	-0.241**		-0.254**
	(0.1042)		(0.1038)
School grade (mean)		0.193*	0.214**
		(0.0978)	(0.1001)
Interaction effects with reading competence			
(ref.: intermediate track (Realschule))			
lower secondary track (Hauptschule) X reading competence	-0.114		-0.118
	(0.2493)		(0.2486)
higher secondary track (Gymnasium) X reading competence	0.107		0.101
	(0.1014)		(0.1017)
Interaction effects with mathematical competence			
(ref.: intermediate track (Realschule))			
lower secondary track (Hauptschule) X mathematical competence	0.266		0.284
	(0.3127)		(0.3197)
higher secondary track (Gymnasium) X mathematical competence	0.293**		0.297**
	(0.1185)		(0.1178)
Interaction effects with school grade			
(ref.: intermediate track (Realschule))			
lower secondary track (Hauptschule) X school grade (mean)		-0.255	-0.281
		(0.2499)	(0.2565)
higher secondary track (Gymnasium) X school grade (mean)		0.013	-0.022
		(0.1320)	(0.1330)
Constant	9.672***	8.771***	8.888***
	(1.2624)	(1.3147)	(1.3140)
Within-R2	0.1436	0.1426	0.1459
Observations	7,085	7,085	7,085
N	3,045	3,045	3,045

Source: NEPS SUF SC3 9.0.0 (download); doi:10.5157/NEPS:SC3:9.0.0
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors by school level in parentheses; controls: age; age-wave effects; class fixed effects; subjective health status, full regression models are presented in Table A4 in the Appendix.

However, to see whether differences between boys and girls drive the main results presented in Table 3, I tested for further heterogeneity by considering variation by gender in an additional sensitivity check. Results of the sensitivity analyses are presented in Table 5. Fixed-effects regression models underline the positive relationship between children's school grades and reported life satisfaction. As depicted in Model 2c and 3c the effect of school grades remains stable and the interaction term with gender does not suggest differences between girls and boys. However, for the effect of children's academic competencies results suggest differences between girls and boys. While results in the main part do not show differences in children's life satisfaction by academic competence levels, considering differences by gender suggest that higher mathematical competence levels are associated with lower life satisfaction for boys.

Thus, it seems that mathematical competencies are associated with gender-specific experiences affecting girls and boys levels of life satisfaction differently.[8] Therefore, to sum up, sensitivity analyses support hypothesis 1 for girls, but not for boys and suggest that higher competence levels in mathematics are associated with lower life satisfaction levels for the latter. However, they are in line with hypothesis 2 and suggest a positive relationship between school grades and life satisfaction for both boys and girls.

Table 5: Results of Fixed-Effects Regressions Including Heterogeneous Effects by Gender

	Modell 1c	Modell 2c	Modell 3c
Reading competence	0.044		0.043
	(0.0556)		(0.0558)
Mathematical competence	-0.205***		-0.212***
	(0.0689)		(0.0691)
School grade (mean)		0.283***	0.290***
		(0.0940)	(0.0944)
Interaction effects with reading competence (ref.: boys)			
Girls X reading competence	0.090		0.085
	(0.0821)		(0.0820)
Interaction effects with mathematical competence (ref.: boys)			
Girls X mathematical competence	0.380***		0.375***
	(0.1062)		(0.1075)
Interaction effects with school grade (ref.: boys)			
Girls X school grade (mean)		-0.078	-0.117
		(0.1262)	(0.1245)
Constant	9.902***	8.533***	8.596***
	(1.1011)	(1.1528)	(1.1420)
Within-R^2	0.1574	0.1561	0.1613
Observations	7,085	7,085	7,085
N	3,045	3,045	3,045

Source: NEPS SUF SC3 9.0.0 (download); doi:10.5157/NEPS:SC3:9.0.0
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors by school level in parentheses; controls: age; age-wave effects; class fixed effects; subjective health status, full regression models are presented in Table A5 in the Appendix.

5 Discussion and conclusion

The present study aimed at examining the effect of children's competence levels and school grades on life satisfaction in secondary schools. Empirical results contribute to previous literature by addressing methodological shortcomings of prior research, like a scarce number of longitudinal analyses, omitted variable bias, and limitations in causal inference. Moreover, this paper provided insights into differences in the importance of children's academic competencies

[8] The same conclusion remains if gender differences are included in separate regression models instead of interaction effects.

and school grades for their life satisfaction and investigated heterogeneous effects by attended school track. Drawing on information from waves one, three, five, and six of a sample of 3,045 secondary school students of the National Educational Panel Study in Germany (NEPS) results suggest, that it is mainly children's school grades which contribute to their life satisfaction. In line with previous studies and supporting theoretical expectations based on self-determination theory, school grades seem to be positively linked to children's life evaluations (e.g. Edgar et al., 2015; González et al., 2020; Ng et al., 2015; Reysen et al., 2017). Similar to studies in other countries, for example, the United States (e.g. Lyons and Huebner, 2016; Reysen et al., 2017) or Chile (e.g. González et al., 2020), with comparable operationalizations of the two variables, the effect sizes suggest a small to moderately strong impact of school grades on life satisfaction, regardless of the school track attended. This suggests that, for all children, positive evaluations of school-related performance are important for their life satisfaction.

However, children's levels of academic competencies are only partly related to their life evaluations. While predicted estimates show, that higher competence levels in math decrease children's life satisfaction levels in lower and middle secondary schools and increase children's life satisfaction in higher secondary schools, competence levels in reading seem to be unrelated to children's life evaluations. These results contradict some prior studies (e.g. Chen and Lu, 2009; Lyons and Huebner, 2016; Martin et al., 2014), which might highlight the importance of confounding bias in previous studies. For example, earlier findings suggesting a positive relationship between competencies and children's well-being are not controlled for individual and family-related background characteristics, such as intelligence and socioeconomic background (e.g. Chen and Lu, 2009; Lyons and Huebner, 2016). Additionally, differences compared to prior studies might highlight the importance of the individual's characteristics moderating the relationship. As previous results are often based on samples including older children in secondary school tracks, high schools, or in tertiary education, they indicate differences in the relationship between children's academic competencies and life satisfaction by educational setting and age (e.g. Chen and Lu, 2009; Felsten and Wilcox, 1992; Flett et al., 2009). Thus, compared to prior studies, the present study shows some advantages, since unobserved heterogeneity in time-constant individual characteristics is eliminated by fixed-effects panel regressions and differences between school tracks are examined for children of the same age. Though, also fixed-effect regression estimates can still be biased if there are unobserved time-varying confounding variables.

Differences in the effect of children’s academic competence levels on their life satisfaction by school track also contradict theoretical arguments. As established by human capital theory, higher competence levels are expected to have a positive effect on life satisfaction levels for all children. Thus, especially, the negative relationship between mathematical competencies and life satisfaction for children in lower and middle secondary schools seem to be counterintuitive. However, these results might highlight the consequences of the relationship of high achievement in school and underload in schoolwork for school-related boredom and frustration. As research in high achieving children suggests, the higher capabilities within a context of lower requirements, the higher the probability of being bored and frustrated in the specific context (Feldhusen and Kroll, 1991; Jin and Moon, 2016; Larson and Richards, 1991). This might result in lower life satisfaction, especially if children feel mismatched in their current school track. Thus, the negative effect of mathematical competencies in children attending the lower secondary school tracks might indicate that especially highly competent children in these schools suffer from underload in school-related work and frustration. This point out some consequences of wrong track placement in secondary schools.

In addition to these differences in the effect of children's academic competence levels on their life satisfaction, taking into account the school track attended, sensitivity analyses also show differences between boys and girls. While higher mathematical competencies are negatively associated with life satisfaction for boys, the effect is the opposite for girls. This could indicate gender-related consequences of higher achievement in children’s everyday experiences, as high levels of mathematical competencies are assumed to have a different meaning for boys and girls. It is hypothesized, that higher levels of competence represent higher levels of school engagement, which is more likely to be associated with typical female gender roles. Thus, higher mathematical competence levels for boys might reflect low gender typicality, which could negatively affect their peer relations in school. For example, Bergold et al. (2020) emphasize that high-achieving boys have a higher risk of being bullied at school, which in turn could explain the negative effect on satisfaction.

Although the present study shows some new and interesting insights into the relationship between children’s academic competencies, school grades, and life satisfaction, there are some limitations left to be considered. First, the sample consists only of students without any school change. This might result in a selective sample structure containing individuals, who are more likely to have stable family environments, continuous educational careers, and no residential moves during the observation period. Second, the sample was restricted to students participating in at least two panel waves, which might lead to additional selectivity in the students' sample. For example, students in lower and higher secondary schools are more likely to drop out of the panel than students in middle secondary school track are. Furthermore, students with higher grades in German, lower grades in math, students from the younger half of the sample, and females are more likely to participate in the survey (Steinhauer and Zinn, 2016). Thus, the sample becomes more homogeneous regarding children's competence levels, school grades, and age. This selectivity might affect the results, because of the smaller variance in the respective variables. In this case, the results presented above would be lower-bound estimates and, likely, the effects of children's academic competencies and school grades on life satisfaction are underestimated (Winship and Mare, 1992). Third, the operationalization of children's life satisfaction by only asking one single question raises concerns about the validity and reliability of the measurement, which cannot be directly addressed with NEPS data. It might be possible, that compared to a multi-item measurement the global indicator is less sensitive for changes over time and differences in life satisfaction between children. This would lead to a further reduction of the effect of children's academic competencies and school grades on life satisfaction. Finally, fixed-effect regression estimates can still be biased if there are unobserved time-varying confounding variables. For example, NEPS data do not provide detailed information about parent's employment trajectories, which may both affect children's competence levels, school grades, and life satisfaction.

Notwithstanding these limitations, the study provides deeper insights into the effect of children's competence levels and school grades on their life satisfaction and contributes to the discussion about a causal relationship. Even though the effects of academic competencies and school grades on life satisfaction are possibly underestimated, the study highlights the importance of school grades. The study also points out inequalities between school tracks and gives some hints about the effects of tracking in Germany. Moreover, sensitivity analyses show some differences between boys and girls, which raise the question about the relevance of further mechanisms linking children's academic competence levels to life satisfaction. Thus, further research should replicate these results by using another longitudinal dataset, address underlying mechanisms and make further differences in subgroups to help politicians and professionals in the educational system avoid the long-term consequences of low life- satisfaction early in life such as later life depressive symptoms or anxiety disorders. For example, as suggested by Ocal and Altınok (2016) or Suldo et al. (2013) enhancing service-learning projects which address children's feelings of competence, student-teacher relationship and parental involvement in school might be a potential strategy.

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Appendix

Table A1: Correlation between Reading Competencies and Children's Grades

	GPA German	GPA Math	GPA sum
Reading competence	0.130***	0.088***	0.108***
	(0.0095)	(0.0113)	(0.0087)
R^2- within	0.25	0.26	0.33
R^2- between	0.43	0.31	0.43
Observations	7,085	7,085	7,085
N	3,045	3,045	3,045

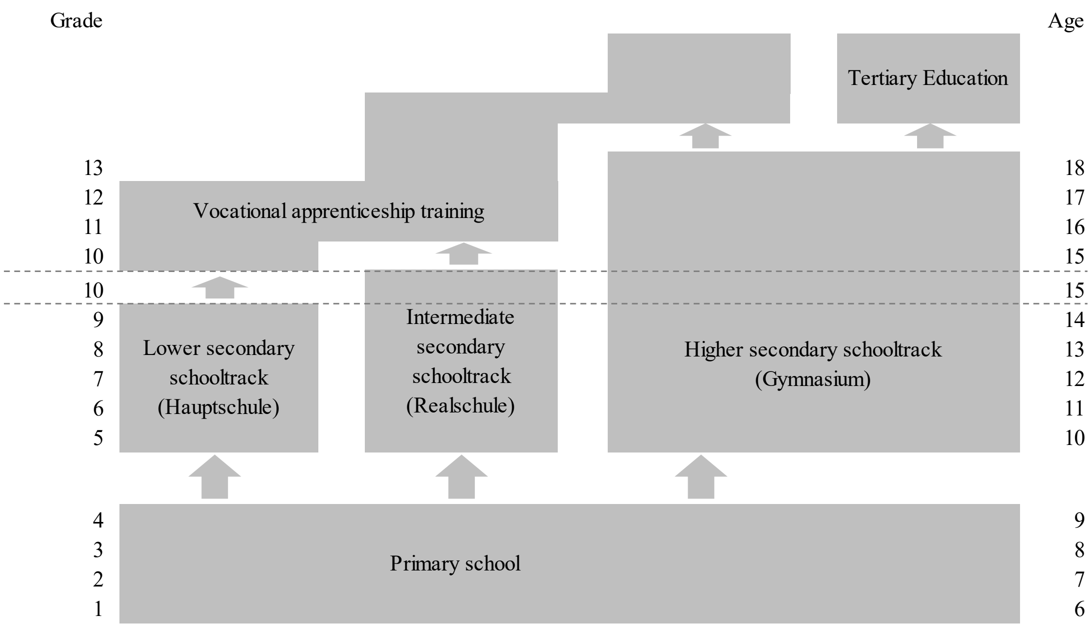
Source: NEPS SUF SC3 9.0.0 (download); doi:10.5157/NEPS:SC3:9.0.0
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors by school level in parentheses; controls: age-wave effects

Table A2: Correlation between Mathematical Competencies and Children's Grades

	GPA German	GPA Math	GPA sum
Mathematical competence	0.089***	0.280***	0.181***
	(0.0107)	(0.0139)	(0.0105)
R^2- within	0.26	0.25	0.32
R^2- between	0.39	0.44	0.47
Observations	7,085	7,085	7,085
N	3,045	3,045	3,045

Source: NEPS SUF SC3 9.0.0 (download); doi:10.5157/NEPS:SC3:9.0.0
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors by school level in parentheses; controls: age-wave effects

Figure A1: German Education System



Source: Kultusministerkonferenz (2019), own adaptation.

Table A3: Fixed-Effects Regression Models for Regression Models 1a to 3a Including Control Variables

	Modell 1a	Modell 2a	Modell 3a
Reading competence	0.072*		0.068
	(0.0426)		(0.0426)
Mathematical competence	-0.016		-0.027
	(0.0513)		(0.0507)
School grade (mean)		0.245***	0.244***
		(0.0631)	(0.0632)
Age	-0.283***	-0.228**	-0.237**
	(0.1001)	(0.1007)	(0.1008)
Wave	-1.006***	-0.794***	-0.823***
	(0.2041)	(0.2004)	(0.2051)
Age X wave	0.071***	0.058***	0.059***
	(0.0124)	(0.0124)	(0.0125)
Self-rated health	-0.596***	-0.582***	-0.582***
	(0.0596)	(0.0598)	(0.0595)
Constant	12.640***	10.825***	10.825***
	(0.9710)	(1.0589)	(1.0584)
Within-R^2	0.1318	0.1352	0.1360
Observations	7,085	7,085	7,085
N	3,045	3,045	3,045

Source: NEPS SUF SC3 9.0.0 (download); doi:10.5157/NEPS:SC3:9.0.0
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors by school level in parentheses, controlled for individual class-level fixed-effects.

Table A4: Fixed-Effects Regression Models for Regression Models 1b to 3b Including Control Variables

	Model 1b	Model 2b	Model 3b
Reading competence	0.009 (0.0895)		0.010 (0.0899)
Mathematical competence	-0.241** (0.1042)		-0.254** (0.1038)
School grade (mean)		0.193* (0.0978)	0.214** (0.1001)
Interaction effects with reading competence (ref.: intermediate track (Realschule))			
lower secondary track (Hauptschule) X reading competence	-0.114 (0.2493)		-0.118 (0.2486)
higher secondary track (Gymnasium) X reading competence	0.107 (0.1014)		0.101 (0.1017)
Interaction effects with mathematical competence (ref.: intermediate track (Realschule))			
lower secondary track (Hauptschule) X mathematical competence	0.266 (0.3127)		0.284 (0.3197)
higher secondary track (Gymnasium) X mathematical competence	0.293** (0.1185)		0.297** (0.1178)
Interaction effects with school grade (ref.: intermediate track (Realschule))			
lower secondary track (Hauptschule) X school grade (mean)		-0.255 (0.2499)	-0.281 (0.2565)
higher secondary track (Gymnasium) X school grade (mean)		0.013 (0.1320)	-0.022 (0.1330)
Age	-0.483* (0.2557)	-0.468* (0.2610)	-0.499* (0.2600)
Interaction effects with age (ref.: intermediate track (Realschule))			
age X lower secondary track (Hauptschule)	0.811* (0.4553)	0.798* (0.4646)	0.822* (0.4530)
age X higher secondary track (Gymnasium)	0.602** (0.2930)	0.591** (0.2980)	0.609** (0.2965)
Wave (ref.: wave 1)			
wave 3	-2.544 (2.7300)	-2.708 (2.7450)	-2.474 (2.7499)
wave 5	-1.893 (3.5056)	-2.594 (3.4837)	-1.877 (3.4907)

Source: NEPS SUF SC3 9.0.0 (download); doi:10.5157/NEPS:SC3:9.0.0
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors by school level in parentheses; controlled for individual class fixed-effects.

Table A4: Fixed-Effects Regression Models for Regression Models 1b to 3b Including Control Variables (continued)

	Model 1b	Model 2b	Model 3b
Interaction effects with wave			
(ref.: intermediate track (Realschule))			
wave 3 X lower secondary track (Hauptschule)	-0.281 (5.1974)	0.057 (5.4510)	-0.128 (5.3890)
wave 3 X higher secondary track (Gymnasium)	2.886 (3.0457)	3.357 (3.0658)	2.903 (3.0621)
wave 5 X lower secondary track (Hauptschule)	7.888 (7.0023)	8.629 (7.1414)	8.075 (6.9155)
wave 5 X higher secondary track (Gymnasium)	3.062 (3.8704)	3.723 (3.8671)	2.891 (3.8689)
Self-rated health	-0.565*** (0.1092)	-0.557*** (0.1134)	-0.548*** (0.1118)
Interaction effects with self-rated health			
(ref.: intermediate track (Realschule))			
self-rated health X lower secondary track(Hauptschule)	-0.196 (0.2771)	-0.204 (0.2723)	-0.214 (0.2759)
self-rated health X higher secondary track (Gymnasium)	-0.016 (0.1310)	-0.017 (0.1346)	-0.023 (0.1326)
Wave-Age Effects			
(ref.: wave 1)			
wave 3 X age	0.254 (0.2346)	0.256 (0.2380)	0.257 (0.2357)
wave 5 X age	0.258 (0.2619)	0.283 (0.2635)	0.267 (0.2623)
Wave-Age Effects by school track			
(ref.: intermediate track (Realschule))			
wave3 X age X lower secondary track (Hauptschule)	-0.070 (0.4263)	-0.089 (0.4458)	-0.088 (0.4411)
wave 3 X age X higher secondary track (Gymnasium)	-0.374 (0.2614)	-0.380 (0.2652)	-0.371 (0.2624)
wave 5 X age lower secondary track (Hauptschule)	-0.755 (0.4641)	-0.788* (0.4738)	-0.776* (0.4625)
wave 5 X age X higher secondary track (Gymnasium)	-0.444 (0.2934)	-0.441 (0.2965)	-0.428 (0.2952)
Constant	9.672*** (1.2624)	8.771*** (1.3147)	8.888*** (1.3140)
Within-R2	0.1436	0.1426	0.1459
Observations	7,085	7,085	7,085
N	3,045	3,045	3,045

Source: NEPS SUF SC3 9.0.0 (download); doi:10.5157/NEPS:SC3:9.0.0
Note: * p < 0.10, ** p < 0.05, *** p < 0.01; clustered standard errors by school level in parentheses; controlled for individual class fixed-effects.

Table A5: Fixed-Effects Regression Models for Regression Models 1c to 3c Including Control Variables

	Modell 1c	Modell 2c	Modell 3c
Reading competence	0.044		0.043
	(0.0556)		(0.0558)
Mathematical competence	-0.205***		-0.212***
	(0.0689)		(0.0691)
School grade (mean)		0.283***	0.290***
		(0.0940)	(0.0944)
Interaction effects with reading competence (ref.: boys)			
girls X reading competence	0.090		0.085
	(0.0821)		(0.0820)
Interaction effects with mathematical competence (ref.: boys)			
girls X mathematical competence	0.380***		0.375***
	(0.1062)		(0.1075)
Interaction effects with mathematical competence (ref.: boys)			
girls X school grade (mean)		-0.078	-0.117
		(0.1262)	(0.1245)
Age	0.022	0.028	0.035
	(0.1370)	(0.1374)	(0.1349)
Interaction effects with mathematical competence (ref.: boys)			
girls X age	-0.141	-0.136	-0.148
	(0.2402)	(0.2445)	(0.2422)
Wave (ref.: wave 1)			
wave 3	-0.384	-0.376	-0.245
	(0.3016)	(0.2956)	(0.3021)
wave 5	-0.242	-0.343	-0.075
	(0.5412)	(0.5288)	(0.5405)
Interaction effects with wave (ref.: boys)			
girls X wave 1	-0.445	-0.139	-0.493
	(0.5192)	(0.5122)	(0.5220)
girls X wave 5	-0.598	-0.005	-0.674
	(0.9639)	(0.9517)	(0.9685)
Self-rated health	-0.536***	-0.517***	-0.519***
	(0.0761)	(0.0770)	(0.0763)
Interaction effects with self-rated health (ref.: boys)			
girls X self-rated health	-0.068	-0.082	-0.075
	(0.1062)	(0.1083)	(0.1056)
Constant	9.902***	8.533***	8.596***
	(1.1011)	(1.1528)	(1.1420)
Within-R^2	0.1574	0.1561	0.1613
Observations	7,085	7,085	7,085
N	3,045	3,045	3,045

Source: NEPS SUF SC3 9.0.0 (download); doi:10.5157/NEPS:SC3:9.0.0

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors by school level in parentheses; controlled for individual class fixed-effects.

Chapter 3 – The intervening role of social relationships in the effect of education on mental health (Article 2)

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Status: Unsubmitted

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Abstract
This paper contributes to literature examining the interplay of education, social relationships and mental health. Based on social network theories and studies linking social capital to health, we argue that the number of social relationships play a role in explaining the link between education and mental health. Using data from the German panel study "Labour Market and Social Security" (PASS) conducted from 2006/2007 to 2018, our sample comprises 24,450 individuals observed in 3.5 waves on average. By way of random-effects panel regression models, we estimate the association between education and individuals' probability of reporting at least good mental health. Based on mediation analyses, we identify the mediating effect of the individuals' number of social relationships measured by their overall level of social integration, marital and cohabitation status, number of close friends and relatives, and active membership in a voluntary association. Results show that individuals with higher education are more likely to report a higher number of social relationships and that the number of social relationships explains some aspect of the positive link of education to mental health. In particular, a person's overall level of social integration and the number of close friends and relatives outside the household contribute to the total effect of education on mental health. In addition, when using individuals' overall health status as an alternative outcome variable, we see significant differences; this raises concerns about the importance of the number of social relationships for an individual's general health. Except for the number of close friends and relatives outside the household, we find that social relationships do not act as a mediator. Thus, we conclude that mediation via the number of social relationships seems to be relevant for mental health, but is not equally important for an individual's overall health status.

1 Introduction

Educational inequalities in mental health are a well-established phenomenon and individuals with lower levels of education tend to be at higher risk for poor mental health. This holds true for different countries and mental health indicators (Fryers et al., 2003; Halpern-Manners et al., 2016). For example, studies conducted in Australia, the UK, the US, and the Netherlands investigating the relationship in adults, report that individuals with a maximum of 11 years of schooling are more than twice as likely to suffer from an anxiety disorder and have a higher 12-months prevalence of experiencing mood disorders, such as depression. In addition, they demonstrate a higher prevalence of affective disorders in individuals who have obtained at most a high school degree or lower (for review see Fryers et al., 2003). Furthermore, a meta-analysis shows that one more year in education decreases the risk of having depressive symptoms by about 3 percent on average (Lorant et al., 2003). Thus, being mentally ill seems to be a particular concern for poorly educated people.

Having a mental disorder has far-reaching consequences for an individual's life by making it difficult to remain physically healthy, reducing quality of life, and leading to lower life expectancy (Liu et al., 2017; OECD, 2021; World Health Organization, 2019). For this reason, understanding educational differences in mental health is of increasing scientific interest, as such an understanding helps to identify valuable strategies for mitigating these disparities. One strategy to reduce the negative consequences of lower education is to address key mechanisms that link education to mental health. In doing so, social resources, such as social support through social relationships, are often highlighted as significant factors (Berkman et al., 2000; Ross and Wu, 1995; Thoits, 2011). The main argument is that, based on different education levels, individuals have access to different numbers, types, and qualities of social relationships, which, among other things, result in different levels of social support and, consequently, are linked to diverging mental health outcomes (e.g. Murrell and Meeks, 2002; Vonneilich et al., 2012). This is because higher levels of social support increase an individual's potential to cope with stressful life events, compensate for the lack of own resources, and foster feelings of being loved and cared for (Berkman et al., 2000; Thoits, 2011). The number of social relationships is therefore expected to mediate the effect of education on mental health.

Nevertheless, except for a small number of studies addressing the mediation role of social relationships on the effect of education on individuals' overall health status (e.g. Antonucci et al., 2003; Ettner and Grzywacz, 2003; Murrell and Meeks, 2002; Vonneilich et al., 2012), the mediating role of social relationships in the effect of education on mental health has hardly been investigated empirically. To the best of our knowledge, there are only three studies that evaluate the mediation effect of social relationships with regard to mental health in particular, and these studies show conflicting results. For instance, based on an adult sample in Kentucky (U.S.), Murrell and Meeks (2002) investigate how social support, measured by a scale considering individuals' functional or perceived level of support from weak and strong social relationships, mediates the effect of individuals' years of education on fatigue. They show that social support explains a small part of the education's effect on mental health. In addition, two other studies provide deeper insights into the mediation effect of the number of social relationships regarding the link between education and depression (Ettner and Grzywacz, 2003; Lee, 2011). Ettner and Grzywacz (2003) show that a combined measurement of the number of social relationships– including an individual's marital status, their number of children, and friends – seems to provide no clear evidence of a mediation effect in an adult sample from California (U.S.). In contrast, Lee (2011) indicates that the overall level of social relationships, again measured by an individual's marital status, their number of children, living siblings, having close friends, participation in the labor market, and participation in voluntary associations, explains some part of the relationship between different levels of education and depression in a sample based on the South Korean adult population.

However, there are still some uncertainties regarding the mediation of social relationships, and we address these in the following study. First, since all three studies mentioned above refer to either depression or fatigue, the relevance of mediation for other dimensions of mental health (such as anxiety or a person's general mental health status) is still unclear. Therefore, we contribute to the existing research by focusing on individuals' global self-assessments of their overall mental health status. Second, previous investigations have not yet addressed the question of whether all types of social relationships contribute to the relationship. Although there are theoretical distinctions between different types of social ties, namely strong and weak ties (Granovetter, 1973; Thoits, 2011), previous research does not show whether both types mediate the effect of education on mental health in the same vein. While Murrell and Meeks (2002) only focus on social support and do not address the mediation effect via social relationships, Lee (2011) and Ettner and Grzywacz (2003) investigate the mediation effects considering only combined measurements. Therefore, we transcend these previous results by examining different types of social relationships. In addition to a summary index of social integration, we show whether marital and cohabitation status, the number of close friends and relatives outside the household, or active membership in voluntary associations equally mediates the effect of education on mental health. Third, we seek to overcome the methodological limitations of previous mediation analyses. For example, Lee (2011) may have overestimated the mediation effect as she included individual levels of labor market participation in the summary index, which may reflect another mechanism that is different from social relationships. We avoid such an overestimation of the mediation effect by using a summary index that does not include any other mediators unrelated to the concept of social relationships. Another limitation occurs in the study of Ettner and Grzywacz (2003), who used relative risk ratios to compare changes and differences in the significance of coefficients to examine mediation effects. Recent methodological research has shown that such model comparisons are biased (Breen et al., 2018). We avoid this problem by using linear probability models that do not have such a methodological limitation.

In the present study, we used data from the panel study "Labour Market and Social Security" (PASS) in Germany, which provides rich information on individuals' social relationships and health. We analyzed a sample that consists of two different subsamples, with one being representative of the German working-age population and the other referring to recipients of welfare benefits. The sample of welfare recipients includes a large number of individuals with extremely low levels of education, thus ensuring that the data contains all educational groups to a satisfactory extent. For this study, we used the information of adults aged between 30 to 60 years and estimated linear random-effects panel regression models. In our mediation analysis, we followed the procedure originally proposed by Baron and Kenny (1986) and added advanced strategies as suggested by VanderWeele (2015). We investigated the total effect of education on mental health, and report direct and indirect effects, and in addition, we tested for the statistical significance of the indirect effects using the test proposed by Sobel (1982). This is necessary to determine whether there is a mediation effect, especially since some of the previous literature suggests only weak mediation effects via social relationships (e.g. Ettner and Grzywacz, 2003; Murrell and Meeks, 2002). Finally, we included some sensitivity analyses. As suggested by VanderWeele (2015), we estimated fixed-effects regression models for parts of our analysis to check whether our results are robust when eliminating time-constant unobserved confounding variables. In addition, we replicated our results for individuals' overall health status to see whether our conclusions hold to the same extent when considering other dimensions of individuals' health status that are strongly related to mental health.

2 Theoretical considerations and hypotheses

Education, which in the following refers to an individual's level of general and vocational education, is assumed to be a very important determinant for mental health, and a higher number of social relationships could explain certain aspects of the relationship between education and mental health. Different theoretical approaches exist which explain the relationship between education and mental health. These are based on economic, sociological, and psychological theories and follow the argument that higher education leads to higher levels of various resources and, therefore, positively influences individuals' mental health (Bartley, 2017; Grossman, 2006). For example, education is related to higher levels of labor market-related outcomes, as well as social and psychological resources, which are all beneficial for mental health (Grossman, 2006; Lin, 2002; Ryan and Deci, 2000). Social relationships, which refer to "connections to and contacts with other people" (Thoits, 2011), can be seen as one component of social resources. They can be divided into strong and weak social relationships, with strong social relationships referring to individuals' relationships with members of small, intimate, and informal groups (e.g., families and peer groups) and weak social relationships signifying contacts with people from larger, more institutionalized, and more formal networks (e.g. colleagues from work, members in voluntary associations) (Granovetter, 1973; Thoits, 2011). In the following, we explain how social relationships may act as mediators in the relationship between education and mental health. We begin by presenting arguments on how education affects social relationships and then address the question of how social relationships affect mental health.

Social relationships can be expected to mediate the effect of education on mental health because education affects the number of social relationships (Erickson, 2004; Gesthuizen et al., 2008). This is, firstly, because individuals with different levels of education fundamentally differ in their opportunities to encounter others. The number of social relationships depends on the probability of meeting various other people in different social circles, which correlates to the number of different settings one participates in (Erickson, 2004). Higher educated individuals have attended a larger variety of educational settings (e.g. Jusri and Kleinert, 2018) and are involved in more formal settings (e.g. Erickson, 2004; Gesthuizen et al., 2008; Klein, 2015). For instance, they will likely have attended different types of school, have completed vocational training or a university degree, and are more likely to participate in the labor market, all of which increases the probability of establishing contact with a large number of different other individuals, potential cohabitants or confidants (Erickson, 2004). Therefore, different probabilities to meet different other individuals should increase the number of weak and strong social relationships of higher educated individuals.

Secondly, differences in educational level should also lead to differences in the number of social relationships, as education affects the social attractiveness of individuals. The higher the level of education, the higher the social status, prestige, and associated resources (Bourdieu, 1983; Bourdieu and Passeron, 1970; Erickson, 2004). Therefore, individuals with higher levels of education are assumed to be strongly attractive network partners to others with similar or lower levels of education (Erickson, 2004). It is assumed that others have a high interest in networking with them or in building strong social relationships (Erickson, 2004; Lin, 2000). Therefore, it should be easier for better educated people to find access to new social networks, meet a potential partner, or find new friends. As a result, individuals with higher levels of education should have a higher number of weak and strong social relationships due to their higher level of social attractiveness.

Thirdly, education is also expected to affect an individual's number of social relationships through higher levels of social and verbal skills (Hsung and Lin, 2008), as higher levels of social and verbal skills help to establish in contact and to maintain social connections and thus lead to increased levels of social relationships. For instance, individuals with better social and verbal skills are more likely to initiate social contact effectively and appropriately. Moreover, better social and verbal skills lead to a higher number of social relationships because they help to maintain social connections. For example, they foster individuals' abilities to adapt their behavior to a specific situation, to react accordingly, and to realize goals in social interactions (Merrell and Gimpel, 2014). All of this increases individuals' competence to communicate effectively and manage social conflicts (Amato, 1996), and fosters their abilities to overcome disagreements, disputes, and problems in a social relationship more easily. This should, in turn, lead to higher levels of weak social relationships, because individuals are more easily able to form large social networks with diverse others. In addition, this should also increase the number of strong social relationships, because it helps to avoid marital dissolution, family conflicts, or friendship breakdown. Therefore, based on higher levels of social and verbal skills, higher educated individuals are assumed to generate a higher number of weak ties and to maintain a higher number of strong social relationships.

Finally, the better educated individuals are assumed to have higher levels of weak social relationships, in particular because they have more resources to share with others and seek social relationships which perpetuate their social status (Gesthuizen et al., 2008). As a result, they invest strongly in social activities which are more publicly visible and, therefore, more strongly invest in weak ties. In contrast, individuals with lower levels of education can be expected to invest more in strong ties because their lack of resources prevents them from investing in weak social relationships or improving their social status. Thus, they mostly lack weak social relationships (Gesthuizen et al., 2008). Consequently, higher educated individuals should have a higher number of weak social ties.

In summary, higher educated individuals are expected to profit from higher numbers of strong and weak social relationships. This brings us to our first hypothesis:

H1: The higher the individuals' educational levels the higher their number of strong and weak social relationships.

The different levels of strong and weak social relationships by education, in turn, should result in different levels of individual mental health, because, among other things, they provide different levels of social support and social reputation. Strong social relationships are positively linked to individuals' mental health, because they increase the feeling of being loved and cared for, and the feeling of security in uncertain situations. Moreover, they reinforce an individual's sense of identity and recognition. In addition, strong social relationships prevent negative mental health outcomes, as they provide high levels of emotional support and protect from negative emotional consequences of stressors, thus de-escalating emotional strain of daily challenges (Berkman et al., 2000; Thoits, 2011). Furthermore, close relatives and friends are assumed to reduce an individual's symptoms of anxiety, depression, and psychological distress in case of critical life events, because they provide, for example, material support in case of need and, thus, compensate for the loss of resources, such as income. Finally, strong ties should lead to better mental health, because they may motivate individuals to take better care of themselves by, for example, encouraging, persuading, reminding, or pressuring a person to adopt positive practices (Thoits 2011; Berkman et al., 2000; Umberson et al., 2010). Consequently, we expect that a higher number of strong social relationships leads to better mental health.

Weak social relationships reduce negative mental health consequences of harmful conditions, because they provide informational support and social influence. For instance, they enable better access to information about previously unknown options, chances, and assistance from helpful others, which would be otherwise not available (Thoits, 2011). They also increase an individual's ability to better inform themselves about positive factors affecting mental health, and enable contact with others in order to seek appropriate help in uncertain situations or after critical life events, all of which positively affects individuals' mental health outcomes. In addition, weak ties can be expected to positively impact mental health because they provide social influence on important agents (Lin, 2002). They increase individuals' power and their influence on decision-making processes, which, for example, positively affects hiring processes or access to new organizational structures, such as medical health care or other services (Lin, 2002). This may prevent a person from becoming or remaining unemployed, and likely increases their access to more positive working conditions, higher standard of living, or qualitative medical health care (Cohen et al., 2001; Thoits, 2011), factors all associated with better mental health. Thus, we assume that weak social relationships positively affect individuals' mental health.

Based on the aforementioned arguments, different numbers of social relationships should explain some part of educational differences in mental health. While higher educated individuals have a higher number of social relationships and mentally benefit from increased levels of social support, recognition and social influence, lower educated individuals lack these resources and, thus, suffer more severely from daily distress, critical life events, and harmful conditions. Therefore, they have decreased levels of mental health, which leads us to our second hypothesis:

H2: The positive effect of education on mental health is partly mediated by the number of strong and weak social relationships.

3 Data and methods

3.1 Data

We tested these hypotheses with panel data from the study "Labour Market and Social Security" (PASS) of the Institute for Employment Research (IAB) in Germany. The PASS data allows detailed analyses of inequalities in education, health, and social relationships as it provides frequently measured information on individuals' social relationships and health and includes a sufficient number of the most vulnerable groups. The PASS contains two subsamples, the first sample being drawn from individuals in households receiving welfare benefits (so-called Unemployment Benefit II) and the second sample consisting of individuals from the general population in Germany. With its focus not only on the general population but also on the special subgroup of recipients of unemployment benefits, PASS includes a satisfactory number of individuals with low levels of education containing information on 46.000 individuals.

For our analyses, we used waves 1 to 12 (2006/2007 to 2018) of both subsamples. However, we made some restrictions on the sample. For one, we only considered individuals aged 30 up to 60, to ensure that the majority of respondents had completed education and to avoid the mortality-based selection process in higher age groups. Also, we only included individuals in our analyses who were observed at least twice during the observation period and dropped all cases with missing values in the dependent, independent, or control variables. This result in a sample of 85,881 observations from 24,450 individuals (observed at 3.5 times on average), with about 16,037 individuals included in the sample of recipients of welfare benefits (subsample 1) and about 3,508 included in the general population sample (subsample 2). Detailed information on the sample characteristics can be found in Table S1 and Table A3 in the Appendix.

3.2 Operationalization

To measure our main independent variable, namely individuals' levels of education, we used the respondent's *years of education* derived from their highest educational qualification including general and vocational certificates. The measure is calculated by individuals' highest general educational level and years of different types of vocational education, such as training as a semi-skilled worker, apprenticeship, or vocational school attendance (Berg et al., 2020). The years of education ranges from 7 to 21, and is about 13 years for the general population sample and about 12 years for the sample of recipients of welfare benefits (see Table A3 in the Appendix).

We measured mental health by using a well-established question addressing an individual's subjective mental health status, which not only indicates their overall mental health but also strongly correlates with morbidity rates and is a good predictor for different types of mental disorders (Ahmad et al., 2014; Mawani and Gilmour, 2010). Respondents were asked: "How strongly have you been affected by mental problems, such as fear, dejection or irritability in the past 4 weeks? Please tell me, whether you were affected 'not at all', 'a little bit', 'moderately', 'quite a bit' or 'extremely'?". In the style of previous studies using self-rated health measurements, we dichotomized individuals' mental health status and created a variable indicating individuals with *at least good mental health*. We distinguished between respondents who stated that they were "not at all" or only "a little bit" affected by mental health problems and those who reported being at least moderately affected. Descriptive statistics are presented in Table A3 of the Appendix.

Our analyses of the mediation effect of education via the number of social relationships firstly relied on a social integration index developed by Berkman et al. (2004), which represents someone's overall *level of social integration* into strong and weak social relationships. The index covers an individual's family status, the number of close relatives and friends outside the household, and the individuals' active participation in voluntary associations. Following Berkman et al. (2004) and Vonneilich et al. (2012), we score individuals by characteristics of their networks in each of these dimensions (for detailed information see Table A2 of the Appendix). The index ranges from 0 to 6 (see Table A3 of the Appendix), while "0" indicating social isolation and "6" reflecting a very high level of social integration. Thus, higher ranges in the index reflect a higher number of social relationships.

Secondly, to investigate the relevance of the number of strong social relationships for the indicators included in the index separately (for an overview see Table A3 of the Appendix), we used a dummy variable that indicates whether the individual is *married or cohabited* and provide logarithmic number of *close friends and relatives outside the household*. We logarithmized the values because the relative importance of one additional strong tie arguably decreases with the number of close friends and relatives. We added the value 1 to the number of strong relationships in advance to keep the individuals without friends in our sample.

Thirdly, in order to obtain deeper insights into the relevance of the number of weak social relationships, we used "*active membership in a voluntary association"*, which is a common operationalization of this concept (e.g. Ruiter and Graaf, 2009). We built a variable indicating whether someone actively participates in at least one of the following voluntary association: a labor union, a political party, a church congregation, a sports, music, or cultural club, or an association of another kind.[9]

3.3 Empirical strategy

To investigate the mediation of the effect of education on reporting good mental health via the number of social relationships, we deployed panel regression models based on the random-effects (RE) approach. Given that our outcome variable is binary, we used linear probability models, which are an appropriate alternative to logistic regression models (Breen et al., 2018) and provide some advantages for our analyses: first, the coefficients between different models are highly comparable and, thus, changes implicate a real change in the coefficient. Second, linear probability models are much easier to interpret since they produce consistent estimates of the probability scale (Breen et al., 2018). Therefore, our baseline model is as follows:

[9] Besides including number of social relationships as mediators into the model, we also tested the empirical relevance of the theoretical link between education, social support, and mental health. Results indicate that social support mediates some part of the relationship between education and mental health (see Table A14 to Table A17 of the Appendix). However, fixed effects regressions suggest that time-constant factors partly induce a spurious relationship (see Table A18 of the Appendix).

$$mhealth_{it} = edu_{it}\beta_1 + gender_i\beta_2 + migration\ background_i\beta_3 + SES_i\beta_4 + sample_i\beta_5 + children_{it}\beta_6 + state\ of\ residence_{it}\beta_7 + agegroup_{it}\beta_8 + wave_{it}\beta_9 + c_i + u_{it} \quad (1)$$

$mhealth_{it}$ is the outcome variable and edu_{it} is the focal independent variable of each individual i at time t. β_1 is the coefficient to be estimated that reflects the effect of education. u_{it} refers to the idiosyncratic error term based on variation between individuals and time. c_i captures the time-constant individual-specific error-component. The RE estimator makes the strict exogeneity assumption that both error components, u_{it} and c_i, are uncorrelated with education as the central independent variable of interest and the outcome variable (Brüderl and Ludwig, 2015). This assumption is often violated and one could argue that fixed-effects panel regressions provide a better alternative. In contrast to the RE specification, the fixed-effects approach eliminates the unobserved time-constant characteristics. However, the fixed-effects approach is not appropriate in our case, as the variation in education, our focal independent variable, is very small and the estimated effect of education would only be based on a selective group of adults with changes in education. Thus, we had to apply the random-effects estimation.

In order to make the exogeneity assumption more plausible, we included observed confounding variables, which are expected to affect both education and mental health. We included time-constant and time-varying control variables and controlled for the following time-constant characteristics: *gender*, *migration background*, *socio-economic background (SES)* and *sample affiliation* (PASS welfare benefit recipients sample = 1, general population sample = 0). In addition, we adjusted for the following time-varying confounders: the *number of children*, current *state of residence* (West Germany = 1, East Germany = 0), *age groups*, and *survey waves*. Detailed information on distribution measures regarding our controls is provided in Table A1 of the Appendix. In order to avoid over-control bias (Elwert and Winship, 2014), we did not control for variables positioned on the causal path between education and mental health (e.g., unemployment, occupational position or household income). Thus, β_1 in equation (1) represents the total effect of education on individuals' mental health.

To test whether individuals' total level of social integration and the different types of social relationships mediate the relationship between education and positive mental health, we followed the strategy suggested by Baron and Kenny (1986) and extended it to the recommendations based on the counterfactual approach of mediation analyses provided by

VanderWeele (2015). In line with Baron and Kenny (1986) we investigated the mediation effect in three steps (for an overview see Figure 1).

Figure 1: Coefficient Estimated in the Mediation Analyses

$$
\begin{tikzcd}
edu_i \arrow[r, "\delta_1"] \arrow[rr, bend left, "\gamma_1"] & socRel_{it} \arrow[r, "\gamma_2"] & mhealth_{it}
\end{tikzcd}
$$

Source: Own illustration.

First, we estimated the effects (δ_1) of education on each of the mediators, here denoted as $socRel_{it}$, which represents the first part of the chain of mediation. $socRel_{it}$ reflects the value of each indicator of an individual i at time point t:

$$
\begin{aligned}
socRel_{it} = {} & edu_{it}\delta_1 + gender_i\delta_2 + migration\ background_i\delta_3 + SES_i\delta_4 \\
& + sample_i\delta_5 + children_{it}\delta_6 + state\ of\ residence_{it}\delta_7 \\
& + agegroup_{it}\delta_8 + wave_{it}\delta_9 + v_i + w_{it}
\end{aligned} \tag{2}
$$

Second, we augmented equation (1) by each mediator ($socRel_{it}$) separately and estimated repeated random-effects models for each of the indicators reflecting the number of social relationships:

$$
\begin{aligned}
mhealth_{it} = {} & edu_{it}\gamma_1 + socRel_{it}\gamma_2 + migration\ background_i\gamma_3 + SES_i\gamma_4 \\
& + sample_i\gamma_5 + children_{it}\gamma_6 + state\ of\ residence_{it}\gamma_7 \\
& + agegroup_{it}\gamma_8 + wave_{it}\gamma_9 + \mu_i + \sigma_{it}
\end{aligned} \tag{3}
$$

This model (3) shows the effect (γ_2) of a mediator ($socRel_{it}$) on mental health ($mhealth_{it}$) , which represents the second part of the chain of mediation. Moreover, model (3) yields the direct effect (γ_1) of education on mental health, i.e. net of the respective mediator ($socRel_{it}$).[10] Calculating the difference between the total and the direct effect ($\beta_1 - \gamma_1$) renders the indirect effect of education on mental health that is mediated via each of the social relationships variables (VanderWeele, 2015). In addition, we tested whether the indirect effect is significantly different from zero by deploying a test proposed by Sobel (1982).

[10] As suggested by VanderWeele (2015), we tested for possible heterogeneity in mediation effects based on the central independent variable. We followed this recommendation and tested whether our results vary by adding an interaction term between education and the mediator to the model. However, since this had no effects on the results of the models, we decided to run the analyses without this interaction term.

The proposed mediation analyses only provides valid results under the assumption that the estimated effects of interest are unbiased by unobserved heterogeneity. However, it is difficult to maintain this assumption in our main analyses because time-constant and time-variant unobserved factors may confound the relationships. To partially address this problem, we employed fixed-effects regressions to eliminate time-constant unobserved factors (for detailed information see Brüderl and Ludwig, 2015). In contrast to our education variable, we assume that the number of social relationships does not suffer from variation issues. When employing the fixed-effect estimator for model (3) we are only able to estimate the effect of social relationships as a time-varying variable. Education is treated as a time-constant variable and eliminated like all other time-constant variables. This helps to approximate a causal interpretation, because only if social relationships are also shown to affect mental health in this part of the analyses, the mediation effects predicted in the main part can be shown to be valid. However, it must be noted that also the fixed-effect regression models also yield biased results in case of unobserved time-varying confounding variables.

4 Results

Our random-effects estimates are presented in Table 1 to Table 3. In a first step, we estimated the total effect (β_1) of education on an individual's mental health status according to equation (1). The result is depicted in Table 1 and indicates a positive association between education and mental health. The higher the number of years of education, the higher the probability of reporting at least good mental health. One additional year of education is associated with an increase in the probability of reporting at least good mental health by about 0.6 percentage points. This means that, for example, individuals with a general high school diploma and a university or master's degree, who have completed 18 years of education, are 6 percent more likely to report good mental health than individuals with a secondary school diploma without vocational training who have undergone 8 years of education (see Figure A1 of the Appendix).

Table 1: The Total Effect of Education on Mental Health (β_1)

	At least good mental health
Years of education	0.0064*** (0.0009)

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors by individuals in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, including all control variables, full regression model is presented in tables A4 to A7 in the Appendix.

In the next step, we investigated the relationship between education and mental health mediated through individuals' numbers of social relationships. Results for the first part of the mediation chain are presented in Table 2. According to equation (2), they provide the effect (δ_1) of education on the four different mediating variables. As expected, years of education are positively associated with individuals' level of social integration, being married or cohabited, their number of close friends and relatives outside the household, and active membership in a voluntary association. For example, one additional year of education increases an individual's level of social integration by about 0.044 points on the 6-point scale. In addition, one additional year of education increases the probability of being married or cohabited by about 0.3 percentage points. Furthermore, each additional year of education increases the number of close friends and relatives outside the household by about 1.5 percentage points. Similarly, the probability of active membership in a voluntary organization increases by 2.4 percentage points with each year of additional education. All of this indicates that an individual's level of education is positively associated with their number of social relationships, thus supporting our first hypothesis.

Table 2: The Effect of Education on the Mediators (δ_1)

	Level of social integration	Married or cohabited	Number of close friends and relatives outside the household (ln)	Active membership in a voluntary association
Years of education	0.0438*** (0.0027)	0.0032** (0.0011)	0.0157*** (0.0014)	0.0242*** (0.0010)

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors by individuals in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, including all control variables, full regression models are presented in tables A4 to A7 in the Appendix.

Since individuals' years of education are positively associated with social relationships, we continued with the second part of our mediation analyses. Table 3 presents the results of this second part of the chain of mediation, which is the effect (γ_2) of social relationships on mental health according to equation (3). As theoretically expected, we observe positive associations with an individual's probability of reporting at least good mental health for all mediators. For example, a one-point higher level of social integration is associated with an increase of about 2.3 percentage points in the probability of reporting at least good mental health. In addition, being married or cohabited increases the probability of reporting at least good mental health by about 6 percentage points. Furthermore, increased numbers of close friends and relatives outside the household are associated with better mental health outcomes, and active membership in a voluntary association increases individuals' probability of reporting good mental health by about 2 percentage points. Thus, the results indicate that depending on individuals' educational levels social relationships contribute to mental health.

Table 3: The Effect of Social Relationships on Mental Health Conditioned on Education (γ_2)

	At least good mental health
Level of social integration	0.0230*** (0.0017)
Married or cohabited	0.059*** (0.0050)
Number of close friends and relatives outside the household (ln)	0.0420*** (0.0028)
Active membership in a voluntary association	0.0184*** (0.0038)

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors by individuals in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, including all control variables, separate estimations for each indicator of the number of social relationships, full regression models are presented in tables A4 to A7 in the Appendix.

Since the results presented thus far imply that the first and second conditions of mediation – namely, the influence of education on individuals' number of social relationships and a link between individuals' social relationships and their mental health conditional on education - are fulfilled, we continued with our mediation analysis. In Table 4 we decompose the total effect of education on mental health (β_1) into the direct effect (γ_1) of education on mental health, i.e. net of the mediator, and the indirect effect ($\beta_1 - \gamma_1$). We examined the statistical significance of the indirect effects using the test proposed by Sobel (1982). For all indicators reflecting an individual's number of social relationships, we observe only very small changes in the effect of education on mental health, when controlling for social relationships. Thus, there exist only minor indirect effects of education on mental health through social relationships, as the indirect effects of education through the mediators only account for 0.03 to 0.11 percentage points of the total effect.

However, these very small indirect effects have to be regarded in the context of the small size of the overall effect of education on mental health. Taking this relative comparison into account, some of the mediators explain a substantial part of the overall effect of education on mental health (see Table 4, column 4). In particular, the overall level of social integration and the number of close friends and relatives outside the household serve to explain a meaningful proportion of the total effect. The level of social integration, for example, contributes about 17% to the total effect of years of education on individuals' probability of reporting at least good mental health. Likewise, the number of close friends and relatives outside the household contributes to about 11% to the effect. Thus, although there are only minor indirect effects, these two indicators in particular serve to explain a substantial part of the total effect of years of education on good mental health. This supports our second hypothesis.

Table 4: Decomposition of the Effect of Education on Mental Health

Mediator	Total effect of education on mental health β_1	Effect of education on health net of the mediator γ_1	Indirect Effect $\beta_1 - \gamma_1$	Proportion of the indirect effect on the total effect of education
Level of social integration	0.0064*** (0.0009)	0.0053*** (0.0009)	0.0011***	17.19%
Married or cohabited	0.0064*** (0.0009)	0.0061*** (0.0009)	0.0003*	4.69%
Number of close friends and relatives outside the household (ln)	0.0064*** (0.0009)	0.0057*** (0.0009)	0.0007***	10.94%
Active membership in a voluntary association	0.0064*** (0.0009)	0.0059*** (0.0009)	0.0005***	7.81%

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual, separate estimations for each indicator of the number of social relationships.

Our results based on random-effects regressions reveal statistically relevant mediation effects via the investigated facets of social relationships. They also highlight the importance of an individual's overall level of social integration and the number of close friends and relatives outside the household. However, our results may be biased through unobserved heterogeneity. Therefore, we partly tested for potential confounding in the mediation effect. The results of the fixed-effects regression models support statistically significant effects of individuals' overall level of social integration, the number of close friends and relatives outside the household and an individual's active membership in a voluntary association on their mental health, but do not support the relevance of being married or cohabited (see Table 5). In addition, compared to the random-effects regression models, fixed-effects regressions indicate smaller effects of social relationships on individuals' probability of reporting at least good mental health. For instance, regarding the level of social integration, the coefficient reduces considerably in size. Compared to the random-effects model, which indicates an increase of an individual's probability of reporting at least good mental health by about 2.3 percent if the scores increases by one, fixed-effects regression results only suggest an increase by about 0.7 percentage points. Furthermore, the effect of the number of friends and close relatives outside the household is half as large. This implicates that time-constant factors confound our analyses presented above to some extent. Nevertheless, they indicate that individuals' overall level of social integration, number of close friends and relatives outside the household, and active membership are empirically important aspects of mental health. Therefore, these indicators in fact might also empirically represent mediators within the relationship between education and mental health.

Table 5: Results of the Fixed-Effects Regressions for the Effect of Social Relationships on Mental Health

	At least good mental health	
	RE	**FE**
Level of social integration	0.0230*** (0.0017)	0.0068** (0.0025)
Married or cohabited	0.059*** (0.0050)	0.0034 (0.0094)
Number of close friends and relatives outside the household (ln)	0.0420*** (0.0028)	0.0204*** (0.0037)
Active membership in a voluntary association	0.0184*** (0.0038)	0.0126* (0.0050)

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual, separate estimations for each indicator of the number of social relationships, full regression models are presented in tables A4 to A7 and Table A8 in the Appendix.

5 Sensitivity analyses

Although our empirical analyses presented thus far suggest that the number of social relationships partly mediates the effect of education on mental health, it is unclear whether a similar conclusion could be drawn for individuals' overall health status. An individual's self-rated overall health status is highly related to their mental health and reflects physical and mental components of health (e.g. Bailis et al., 2003). Thus, similar mediators might be relevant. However, for an individual's self-rated overall health status, previous research shows mixed evidence regarding mediation effects, mostly indicating zero or very small positive effects without testing the relevance of each indicator separately (Antonucci et al., 2003; Ettner and Grzywacz, 2003; Murrell and Meeks, 2002; Vonneilich et al., 2012). Therefore, we replicated our findings for the individuals' probability of reporting at least good overall health.

Our results reveal a statistically significant effect of education on reporting at least good health (see Table 6, column 1). Each additional year in education is associated with an increased probability of 1.5 percentage points. This indicates that individuals with a general high school diploma and a university or master's degree (18 years of education) are about 15% more likely to report good health than individuals with a secondary school diploma without vocational training (8 years of education). However, in comparison to the results for mental health, social relationships seem to play a subordinated role. Although, compared to our main analyses, the indirect effects are of similar size, they explain only a very small part of the total effect of education on good health (0.66% to 4.64% of the total effect), given the larger effect of education. In addition, fixed-effects regression results raise doubts concerning the mediation of social relationships in the effect of education on individuals' overall health (see Table 7). Only the effect of the number of close friends and relatives outside the household on individuals' health remains statistically significant, suggesting that only the number of strong ties seem to contribute to the effect of education on health, which underlines the importance of those social relationships for both health outcomes. However, for individuals' overall health status, we conclude that, in contrast to individuals' mental health, social relationships seem to be a less important mediator.

Table 6: Robustness Check for Individuals Overall Health Status

Mediator	**Total effect of education on health** β_1	**Effect of social relationships on health conditioned on education** γ_2	**Effect of education on health net of the mediator** β_2	**Indirect Effect** $\beta_1 - \beta_2$	**Proportion of the indirect effect on the total effect of education**
Level of social integration	0.0151*** (0.0009)	0.0146*** (0.0017)	0.0144*** (0.0010)	0.0007***	4.64%
Married or cohabited	0.0151*** (0.0009)	0.03493*** (0.0051)	0.0150*** (0.0009)	0.0001**	0.66%
Number of close friends and relatives outside the household (ln)	0.0151*** (0.0009)	0.0304*** (0.0028)	0.0146*** (0.0010)	0.0005***	3,31%
Active membership in a voluntary association	0.0151*** (0.0009)	0.0149*** (0.0039)	0.0148*** (0.0010)	0.0003**	1.99%

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual, separate estimations for each indicator of the number of social relationships, full regression models are presented in tables A9 to A12 in the Appendix.

Table 7: Results of the Fixed-Effects Regressions for the Effect of Social Relationships on Overall Good Health

	At least good overall health
Level of social integration	0.001 (0.0026)
Married or cohabited	-0.012 (0.0096)
Number of close friends and relatives outside the household (ln)	0.014*** (0.0036)
Active membership in a voluntary association	0.006 (0.0050)

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450, separate estimations for each indicator of the number of social relationships.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual, full fixed effects panel regression models are presented in Table A13 in the Appendix.

6 Discussion and conclusion

In this study, we investigated the mediating link of social network characteristics in the education–health relationship. Contributing to previous literature, we focused on the link between education and mental health via the number of social relationships. By using data from the Panel "Labour Market and Social Security" (PASS) of the Institute for Employment Research (IAB) of the German Federal Employment Agency (BA) we deployed linear probability panel regression models following the random-effects approach. Based on theoretical arguments, we firstly tested the hypothesis that education affects the number of social relationships (H1). Results suggest that an individual's years of education are associated with their level of social integration, the probability of being married or cohabited, their number of close friends and relatives outside the household, and the active membership in a voluntary association. Secondly, we investigated whether social relationships mediate the relationship between education and mental health (H2). Our mediation analyses reveal that the level of social integration, the number of close friends and relatives outside the household, and their active membership in a voluntary association partly explain the link between education and mental health. In particular, strong ties as represented in the number of close friends and relatives seem to be highly important, since they explain about 11% of the total effect of education on mental health. These results are also supported in fixed-effects regressions on the effect of social relationships on mental health, which accounted for time-constant unobserved heterogeneity. Overall, in line with Lee (2011) and Murrell and Meeks (2002) and according to our hypothesis 2, we conclude that social relationships explain some part of the effect of education on individuals' overall mental health status.

However, some limitations should be considered. First, to measure weak ties exclusively by an individual's active membership in a voluntary association might be of decreased informative value. This is, because weak ties might also exist independently of an active membership in a voluntary association, which limits the explanatory value of the constructed variable. Second, although we eliminated time-constant unobserved heterogeneity when estimating the effect of the number of social relationships on individuals mental health in fixed-effect regression models, we were not able to do the same for the whole mediation chain as the education variable did not have sufficient within-variation to implement a fixed-effect estimation for this variable. Moreover, our results are subject to potential bias because of time-varying unobserved heterogeneity. Thus, the results of our mediation analysis should be considered with caution from a causal perspective.

Despite these limitations, however, our study complements previous investigations of the topic and offers important additional contributions to the mediation of the effect of education on mental health through social relationships. Firstly, we move beyond the mediating role of individuals' overall levels of social integration in the effect of education on mental health, as presented by Lee (2011), Murrell and Meeks (2002), and Ettner and Grzywacz (2003), by investigating different aspects of social relationships separately. Our results highlight that the number of close friends and relatives outside the household and the active membership in a voluntary association appear to be important mediators. Secondly, we show that the mediation chain is not only important for individuals' levels of fatigue or depression as suggested by Murrell and Meeks (2002) and Lee (2011), but also for an individual's overall evaluation of their mental health. Thirdly, unlike previous studies, we account for time-constant unobserved heterogeneity in the analysis of the second part of the mediation chain and are able to show that our conclusions did not change by this. Finally, we further contribute to the literature by replicating our results for individuals' overall health status. This provides additional knowledge on closely related dimensions of health. In line with prior research in this area (Antonucci et al., 2003; Ettner and Grzywacz, 2003; Marmot et al., 1998; Vonneilich et al., 2012), we found only very small mediation effects of social relationships in the link between education and health. However, since we tested the mediation chain for each mediator separately and tested for unobserved heterogeneity in some parts of the link, we obtained deeper insights compared to prior studies. We only found support for mediation by individuals' number of close friends and relatives outside the household, which point to higher relevance of other relevant mechanisms referring to individuals' social and human capital in the effect of education on individuals' overall health status.

The in-depth insights of this study raise discussions about the importance of the number of social relationships for the different dimensions of an individual's health. While it seems theoretically and empirically plausible that the number of social relationships partly mediates the effect of education on physical and mental health, the empirical results of the mediation effect on an individual's overall health status cast doubt on a generalized mediation effect. The level of social integration reflected in someone's number of strong and weak ties seems to be less relevant for educational differences in general health, suggesting that the physical health component of this measurement reduces the relative importance of social relationships. In turn, this raises the question of the different channels linking education to physical and mental health and daily functioning. The results suggest that differences between education levels exist for various reasons, depending on the health dimension studied. However, to the best of our knowledge, these differences have hardly been investigated so far. While some studies have examined the relevance of different mediators in the relationship between education and health for various health measures (e.g. Ettner and Grzywacz, 2003; Murrell and Meeks, 2002), they do not provide deeper insights into the relative importance of different mediators for the effect of education on these health indicators. Thus, further research should address the relative importance of different mediators in the education-health relationship. Studies should investigate the contribution of the different pathways linking education to health outcomes simultaneously for overall physical and mental health and daily functioning.

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Appendix

Table A1: Descriptive Statistics of the Sample

		Subsample 1– recipients of welfare benefits N= 16,037				*Subsample 2- General population sample N= 3,508*			
		mean	***sd***	***min***	***max***	***mean***	***sd***	***min***	***max***
Female		0.56				0.56			
With migration background		0.29				0.15			
Socio-economic background (highest educational level of parents)									
max. lower secondary school degree		0.54				0.61			
intermediate secondary education		0.17				0.17			
higher secondary education		0.16				0.16			
other school degree or unknown		0.14				0.06			
Age groups									
30 to 39	*overall*	0.33	0.47			0.22	0.42		
	between		0.47				0.41		
	within		0.17	-0.59	1.25		0.11	-0.28	0.72
40 to 49	*overall*	0.32	0.47			0.40	0.49		
	between		0.42				0.46		
	within		0.26	-0.60	1.24		0.17	-0.10	0.90
50 to 60	*overall*	0.35	0.48			0.37	0.48		
	between		0.45				0.47		
	within		0.20	-0.57	1.27		0.13	-0.13	0.87
West Germany	*overall*	0.67	0.47			0.81	0.39		
	between		0.46				0.39		
	within		0.05	-0.24	1.58		0.02	0.31	1.31
Number of children	*overall*	1.62	1.40			1.65	1.17		
	between		1.44				1.15		
	within		0.34	-3.71	5.62		0.23	-0.35	3.65

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation.

Table A2: Dimensions of Social Integration and Definition of Score Levels

		score points
married or cohabited	no	0
	yes	2
Number of friends and relatives outside the household	0 to 2	0
	3 to 11	1
	more than 12	2
Membership in voluntary association	no	0
	1 association	1
	more than 2 different associations	2

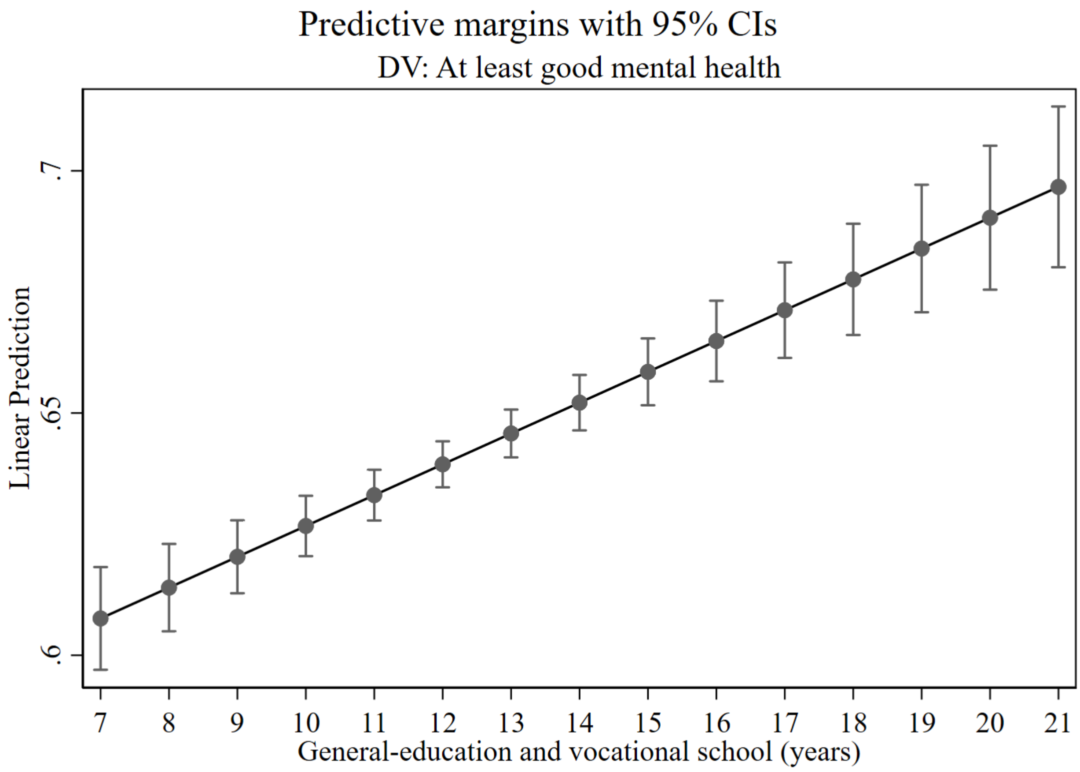
Source: Berkman et al. (2004).

Table A3: Descriptive Statistics of the Main Variables

		Subsample 1– recipients of welfare benefits N= 16,037				***Subsample 2- General population sample N= 3,508***			
		mean	***sd***	***min***	***max***	***mean***	***sd***	***min***	***max***
Years of education	*overall*	11.77	2.66	7	21	12.85	2.88	7	21
	between		2.80	7	21		2.88	7	21
	within		0.21	7.33	15.94		0.08	11.10	14.60
At least good mental health	*overall*	0.60	0.49			0.71	0.46		
	between		0.42				0.41		
	within		0.33	-0.31	1.52		0.22	0.21	1.21
At least good overall health	*overall*	0.40	0.49			0.51	0.32		
	between		0.42				0.29		
	within		0.32	-0.52	1.32		0.16	0.38	1.38
Level of social integration	*overall*	2.60	1.24	1	6	3.57	1.21		
	between		1.16	1	6		1.17		
	within		0.54	-0.84	6.43		0.35	1.57	5.60
Strong social relationships									
Married or cohabited	*overall*	0.53	0.50			0.81	0.39		
	between		0.47				0.39		
	within		0.17	-0.39	1.45		0.07	0.31	1.31
Friends and relatives outside the household	*overall*	7.54	8.09	1	99	7.20	6.91		
	between		8.02	1	99		6.71		
	within		4.86	-55.12	88.67		2.67	-22.30	36.70
Friends and relatives outside the household (ln)	*overall*	1.91	0.64	0.69	4.61	1.83	0.77		
	between		0.60	0.69	4.61		0.73		
	within		0.38	-0.47	4.66		0.31	0.11	3.55
Weak social relationships									
Active membership in a voluntary association	*overall*	0.33	0.47			0.57	0.49		
	between		0.41				0.47		
	within		0.27	-0.58	1.25		0.19	0.07	1.07

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation**.**

Figure A1: Predictive Margins for Reporting at least Good Mental Health by Years of Education



Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation.

Table A4: Random-Effects Regressions for the Mediation of the Level of Social Integration in the Effect of Education on Mental Health Including Control Variables

	Level of social integration	At least good mental health	At least good mental health
Years of education	0.0438***	0.0064***	0.0053***
	(0.0027)	(0.0009)	(0.0009)
Level of social integration			0.0230***
			(0.0017)
Socio-economic background (ref.: parents with low level of education)			
Medium level of education	-0.0227	-0.0028	-0.0025
	(0.0204)	(0.0068)	(0.0068)
Higher level of education	-0.0401	-0.0183*	-0.0173*
	(0.0221)	(0.0074)	(0.0074)
Other degree	-0.1445***	0.0126	0.0157
	(0.0229)	(0.0081)	(0.0081)
Age group (ref.: 30-39)			
40-49	-0.0346**	-0.0179***	-0.0163**
	(0.0130)	(0.0050)	(0.0050)
50-60	-0.0180	-0.0242***	-0.0231***
	(0.0147)	(0.0056)	(0.0055)
West Germany	0.0144	-0.0246***	-0.0248***
	(0.0175)	(0.0056)	(0.0055)
Gender (ref.: male)			
Female	-0.2290***	-0.1114***	-0.1061***
	(0.0140)	(0.0048)	(0.0048)
Migration background	0.1373***	0.0369***	0.0344***
	(0.0161)	(0.0057)	(0.0057)
Sample affiliation (ref.: general population sample)			
PASS welfare benefit recipients sample	-0.9142***	-0.1197***	-0.0984***
	(0.0159)	(0.0053)	(0.0055)
Number of children	0.1492***	0.0054**	0.0012
	(0.0047)	(0.0017)	(0.0017)
Survey wave (ref.: wave 1)			
Wave 2	-0.0725***	0.0181**	0.0204**
	(0.0109)	(0.0063)	(0.0063)
Wave 3	-0.0770***	0.0157*	0.0181**
	(0.0115)	(0.0064)	(0.0064)
Wave 4	-0.0338**	0.0185**	0.0197**
	(0.0126)	(0.0068)	(0.0068)
Wave 5	-0.0466***	0.0304***	0.0316***
	(0.0129)	(0.0065)	(0.0065)
Wave 6	-0.0207	0.0133*	0.0139*
	(0.0134)	(0.0068)	(0.0068)
Wave 7	-0.0504***	0.0197**	0.0207**
	(0.0139)	(0.0068)	(0.0068)
Wave 8	-0.0426**	0.0324***	0.0333***
	(0.0145)	(0.0070)	(0.0070)
Wave 9	-0.0147	0.0357***	0.0359***
	(0.0149)	(0.0070)	(0.0070)
Wave 10	-0.0431**	0.0355***	0.0362***
	(0.0154)	(0.0072)	(0.0072)
Wave 11	-0.0806***	0.0320***	0.0335***
	(0.0157)	(0.0072)	(0.0071)
Wave 12	-0.0536***	0.0333***	0.0341***
	(0.0163)	(0.0074)	(0.0073)
Constant	2.9505***	0.6920***	0.6256***
	(0.0426)	(0.0146)	(0.0154)
Observations	85,881	85,881	85,881
N	24,450	24,450	24,450

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual.

Table A5: Random-Effects Regressions for the Mediation of Being Married or Cohabited in the Effect of Education on Mental Health Including Control Variables

	Married or cohabited	At least good mental health	At least good mental health
Years in education	0.0032**	0.0064***	0.0061***
	(0.0011)	(0.0009)	(0.0009)
Married or cohabited			0.0590***
			(0.0050)
Socio-economic background (ref.: parents with low level of education)			
Medium level of education	-0.0168*	-0.0028	-0.0019
	(0.0079)	(0.0068)	(0.0068)
Higher level of education	-0.0448***	-0.0183*	-0.0157*
	(0.0084)	(0.0074)	(0.0074)
Other degree	-0.0288**	0.0126	0.0141
	(0.0092)	(0.0081)	(0.0081)
Age group (ref.: 30-39)			
40-49	-0.0178***	-0.0179***	-0.0151**
	(0.0049)	(0.0050)	(0.0050)
50-60	-0.0246***	-0.0242***	-0.0205***
	(0.0055)	(0.0056)	(0.0056)
West Germany	-0.0195*	-0.0246***	-0.0226***
	(0.0083)	(0.0056)	(0.0055)
Gender (ref.: male)			
Female	-0.0542***	-0.1114***	-0.1078***
	(0.0054)	(0.0048)	(0.0048)
Migration background	0.1393***	0.0369***	0.0298***
	(0.0064)	(0.0057)	(0.0057)
Sample affiliation (ref.: general population sample)			
PASS welfare benefit recipients sample	-0.2954***	-0.1197***	-0.1017***
	(0.0058)	(0.0053)	(0.0055)
Number of children	0.0570***	0.0054**	0.0005
	(0.0019)	(0.0017)	(0.0018)
Survey wave (ref.: wave 1)			
Wave 2	-0.0135***	0.0181**	0.0200**
	(0.0026)	(0.0063)	(0.0063)
Wave 3	-0.0117***	0.0157*	0.0175**
	(0.0030)	(0.0064)	(0.0064)
Wave 4	-0.0107**	0.0185**	0.0198**
	(0.0037)	(0.0068)	(0.0068)
Wave 5	-0.0092*	0.0304***	0.0312***
	(0.0039)	(0.0065)	(0.0065)
Wave 6	-0.0069	0.0133*	0.0139*
	(0.0042)	(0.0068)	(0.0068)
Wave 7	-0.0061	0.0197**	0.0200**
	(0.0044)	(0.0068)	(0.0068)
Wave 8	-0.0081	0.0324***	0.0328***
	(0.0047)	(0.0070)	(0.0070)
Wave 9	-0.0107*	0.0357***	0.0362***
	(0.0049)	(0.0070)	(0.0070)
Wave 10	-0.0110*	0.0355***	0.0358***
	(0.0052)	(0.0072)	(0.0072)
Wave 11	-0.0130*	0.0320***	0.0324***
	(0.0054)	(0.0072)	(0.0071)
Wave 12	-0.0135*	0.0333***	0.0335***
	(0.0056)	(0.0074)	(0.0073)
Constant	0.7537***	0.6920***	0.6483***
	(0.0173)	(0.0146)	(0.0150)
Observations	85,881	85,881	85,881
N	24,450	24,450	24,450

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual.

Table A6: Random-Effects Regressions for the Mediation of the Number of Close Friends and Relatives outside the Household in the Effect of Education on Mental Health Including Control Variables

	Number of close friends and relatives outside the household (ln)	At least good mental health	At least good mental health
Years of education	0.0157***	0.0064***	0.0057***
	(0.0014)	(0.0009)	(0.0009)
Number of close friends and relatives outside the household (ln)			0.0420***
			(0.0028)
Socio-economic background (ref.: parents with low level of education)			
Medium level of education	0.0346***	-0.0028	-0.0043
	(0.0101)	(0.0068)	(0.0068)
Higher level of education	0.0405***	-0.0183*	-0.0201**
	(0.0110)	(0.0074)	(0.0074)
Other degree	-0.0296*	0.0126	0.0138
	(0.0125)	(0.0081)	(0.0081)
Age group (ref.: 30-39)			
40-49	-0.0320***	-0.0179***	-0.0168***
	(0.0068)	(0.0050)	(0.0050)
50-60	0.0018	-0.0242***	-0.0247***
	(0.0078)	(0.0056)	(0.0055)
West Germany	-0.0458***	-0.0246***	-0.0225***
	(0.0082)	(0.0056)	(0.0055)
Gender (ref.: male)			
Female	-0.0566***	-0.1114***	-0.1092***
	(0.0073)	(0.0048)	(0.0048)
Migration background	0.0398***	0.0369***	0.0353***
	(0.0088)	(0.0057)	(0.0057)
Sample affiliation (ref.: general population sample)			
PASS welfare benefit recipients sample	-0.0818***	-0.1197***	-0.1163***
	(0.0080)	(0.0053)	(0.0053)
Number of children	0.0168***	0.0054**	0.0047**
	(0.0027)	(0.0017)	(0.0017)
Survey wave (ref.: wave 1)			
Wave 2	-0.0286***	0.0181**	0.0194**
	(0.0084)	(0.0063)	(0.0063)
Wave 3	-0.1166***	0.0157*	0.0206**
	(0.0086)	(0.0064)	(0.0064)
Wave 4	-0.1040***	0.0185**	0.0228***
	(0.0087)	(0.0068)	(0.0068)
Wave 5	-0.1410***	0.0304***	0.0359***
	(0.0086)	(0.0065)	(0.0065)
Wave 6	-0.1359***	0.0133*	0.0187**
	(0.0087)	(0.0068)	(0.0068)
Wave 7	-0.1589***	0.0197**	0.0260***
	(0.0088)	(0.0068)	(0.0068)
Wave 8	-0.1516***	0.0324***	0.0384***
	(0.0088)	(0.0070)	(0.0070)
Wave 9	-0.1349***	0.0357***	0.0411***
	(0.0091)	(0.0070)	(0.0070)
Wave 10	-0.1445***	0.0355***	0.0413***
	(0.0091)	(0.0072)	(0.0072)
Wave 11	-0.1441***	0.0320***	0.0375***
	(0.0091)	(0.0072)	(0.0072)
Wave 12	-0.1474***	0.0333***	0.0390***
	(0.0093)	(0.0074)	(0.0074)
Constant	1.9465***	0.6920***	0.6107***
	(0.0223)	(0.0146)	(0.0156)
Observations	85,881	85,881	85,881
N	24,450	24,450	24,450

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual.

Table A7: Random-Effects Regressions for the Mediation of the Active Membership in a Voluntary Association in the Effect of Education on Mental Health Including Control Variables

	Active membership in a voluntary association	At least good mental health	At least good mental health
Years in education	0.0242***	0.0064***	0.0059***
	(0.0010)	(0.0009)	(0.0009)
Active membership in a voluntary association			0.0184***
			(0.0038)
Socio-economic background (ref.: parents with low level of education)			
Medium level of education	0.0149	-0.0028	-0.0031
	(0.0077)	(0.0068)	(0.0068)
Higher level of education	0.0338***	-0.0183*	-0.0189*
	(0.0082)	(0.0074)	(0.0074)
Other degree	-0.0528***	0.0126	0.0136
	(0.0080)	(0.0081)	(0.0081)
Age group (ref.: 30-39)			
40-49	0.0170**	-0.0179***	-0.0182***
	(0.0052)	(0.0050)	(0.0050)
50-60	0.0356***	-0.0242***	-0.0248***
	(0.0058)	(0.0056)	(0.0056)
West Germany	0.0547***	-0.0246***	-0.0256***
	(0.0062)	(0.0056)	(0.0056)
Gender (ref.: male)			
Female	-0.0591***	-0.1114***	-0.1104***
	(0.0052)	(0.0048)	(0.0048)
Migration background	-0.1206***	0.0369***	0.0391***
	(0.0059)	(0.0057)	(0.0057)
Sample affiliation (ref.: general population sample)			
PASS welfare benefit recipients sample	-0.1897***	-0.1197***	-0.1162***
	(0.0060)	(0.0053)	(0.0053)
Number of children	0.0022	0.0054**	0.0053**
	(0.0017)	(0.0017)	(0.0017)
Survey wave (ref.: wave 1)			
Wave 2	-0.0135*	0.0181**	0.0184**
	(0.0055)	(0.0063)	(0.0063)
Wave 3	-0.0032	0.0157*	0.0157*
	(0.0057)	(0.0064)	(0.0064)
Wave 4	0.0220***	0.0185**	0.0181**
	(0.0060)	(0.0068)	(0.0068)
Wave 5	0.0212***	0.0304***	0.0300***
	(0.0060)	(0.0065)	(0.0065)
Wave 6	0.0276***	0.0133*	0.0128
	(0.0062)	(0.0068)	(0.0068)
Wave 7	0.0161*	0.0197**	0.0194**
	(0.0063)	(0.0068)	(0.0068)
Wave 8	0.0222***	0.0324***	0.0320***
	(0.0066)	(0.0070)	(0.0070)
Wave 9	0.0388***	0.0357***	0.0350***
	(0.0067)	(0.0070)	(0.0070)
Wave 10	0.0274***	0.0355***	0.0350***
	(0.0068)	(0.0072)	(0.0072)
Wave 11	-0.0006	0.0320***	0.0320***
	(0.0069)	(0.0072)	(0.0071)
Wave 12	0.0221**	0.0333***	0.0329***
	(0.0071)	(0.0074)	(0.0074)
Constant	0.2224***	0.6920***	0.6881***
	(0.0158)	(0.0146)	(0.0146)
Observations	85,881	85,881	85,881
N	24,450	24,450	24,450

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual.

Table A8: Fixed Effects Panel Regression Results for the Effect of Mediators on Mental Health Including Control Variables

	At least good mental health	At least good mental health	At least good mental health	At least good mental health
Level of social integration	0.0068**			
	(0.0025)			
Married or cohabited		0.0034		
		(0.0094)		
Number of close friends and relatives outside the household (ln)			0.0204***	
			(0.0037)	
Membership in a voluntary association				0.0126*
				(0.0050)
Age group (ref.: 30-39)				
40-49	-0.0107	-0.0107	-0.0099	-0.0109
	(0.0087)	(0.0087)	(0.0087)	(0.0087)
50-60	-0.0216	-0.0215	-0.0212	-0.0217
	(0.0126)	(0.0126)	(0.0126)	(0.0126)
West Germany	0.0198	0.0203	0.0199	0.0211
	(0.0315)	(0.0315)	(0.0315)	(0.0315)
Number of children	-0.0084*	-0.0081*	-0.0082*	-0.0080*
	(0.0040)	(0.0040)	(0.0040)	(0.0040)
Survey wave (ref.: wave 1)				
Wave 2	0.0226**	0.0223**	0.0228***	0.0224**
	(0.0069)	(0.0069)	(0.0069)	(0.0069)
Wave 3	0.0211**	0.0207**	0.0231**	0.0207**
	(0.0072)	(0.0072)	(0.0072)	(0.0072)
Wave 4	0.0294***	0.0293***	0.0315***	0.0290***
	(0.0078)	(0.0078)	(0.0078)	(0.0078)
Wave 5	0.0447***	0.0445***	0.0477***	0.0441***
	(0.0080)	(0.0080)	(0.0080)	(0.0080)
Wave 6	0.0279***	0.0278***	0.0309***	0.0274***
	(0.0083)	(0.0083)	(0.0083)	(0.0083)
Wave 7	0.0371***	0.0368***	0.0404***	0.0366***
	(0.0085)	(0.0085)	(0.0085)	(0.0085)
Wave 8	0.0544***	0.0542***	0.0576***	0.0538***
	(0.0089)	(0.0089)	(0.0089)	(0.0089)
Wave 9	0.0559***	0.0559***	0.0589***	0.0553***
	(0.0093)	(0.0093)	(0.0093)	(0.0093)
Wave 10	0.0568***	0.0566***	0.0598***	0.0561***
	(0.0097)	(0.0097)	(0.0097)	(0.0097)
Wave 11	0.0556***	0.0552***	0.0586***	0.0550***
	(0.0102)	(0.0102)	(0.0102)	(0.0102)
Wave 12	0.0641***	0.0638***	0.0672***	0.0633***
	(0.0106)	(0.0106)	(0.0107)	(0.0106)
Constant	0.5962***	0.6138***	0.5739***	0.6102***
	(0.0256)	(0.0250)	(0.0256)	(0.0246)
Observations	85,881	85,881	85,881	85,881
N	24,450	24,450	24,450	24,450

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual.

Table A9: Random-Effects Regressions for the Mediation of the Level of Social Integration in the Effect of Education on Overall Health Status Including Control Variables

	Level of social integration	At least good overall health	At least good overall health
Years of education	0.0438***	0.0151***	0.0144***
	(16.05)	(15.68)	(14.92)
Level of social integration			0.0146***
			(8.45)
Socio-economic background (ref.: parents with low levels of education)			
Medium level of education	-0.0227	0.00706	0.00725
	(-1.12)	(0.99)	(1.02)
Higher level of education	-0.0401	0.0162*	0.0167*
	(-1.81)	(2.10)	(2.18)
Other degree	-0.145***	-0.00391	-0.00191
	(-6.31)	(-0.48)	(-0.23)
Age group (ref.: 30-39)			
40-49	-0.0346**	-0.0720***	-0.0710***
	(-2.67)	(-13.52)	(-13.35)
50-60	-0.0180	-0.156***	-0.156***
	(-1.23)	(-27.19)	(-27.13)
West Germany	0.0144	-0.0327***	-0.0328***
	(0.82)	(-5.71)	(-5.74)
Gender (ref.: male)			
Female	-0.229***	-0.0668***	-0.0633***
	(-16.31)	(-13.45)	(-12.73)
Migration background	0.137***	0.0452***	0.0436***
	(8.50)	(7.71)	(7.45)
Sample affiliation (ref.: general population sample)			
PASS welfare benefit recipients sample	-0.914***	-0.121***	-0.108***
	(-57.63)	(-22.08)	(-18.91)
Number of children	0.149***	0.00404*	0.00138
	(31.53)	(2.30)	(0.77)
Survey wave (ref.: wave 1)			
Wave 2	-0.0725***	-0.0104	-0.00897
	(-6.67)	(-1.59)	(-1.37)
Wave 3	-0.0770***	-0.0311***	-0.0296***
	(-6.68)	(-4.67)	(-4.43)
Wave 4	-0.0338**	-0.0185**	-0.0177*
	(-2.67)	(-2.67)	(-2.56)
Wave 5	-0.0466***	-0.0171*	-0.0163*
	(-3.62)	(-2.56)	(-2.43)
Wave 6	-0.0207	-0.0301***	-0.0298***
	(-1.54)	(-4.44)	(-4.39)
Wave 7	-0.0504***	-0.0712***	-0.0704***
	(-3.63)	(-10.28)	(-10.17)
Wave 8	-0.0426**	-0.0478***	-0.0472***
	(-2.94)	(-6.75)	(-6.66)
Wave 9	-0.0147	-0.0541***	-0.0539***
	(-0.99)	(-7.45)	(-7.42)
Wave 10	-0.0431**	-0.0617***	-0.0611***
	(-2.80)	(-8.36)	(-8.28)
Wave 11	-0.0806***	-0.0467***	-0.0456***
	(-5.14)	(-6.36)	(-6.22)
Wave 12	-0.0536***	-0.0577***	-0.0570***
	(-3.29)	(-7.65)	(-7.56)
Constant	2.951***	0.502***	0.460***
	(69.29)	(32.77)	(28.65)
Observations	85,881	85,881	85,881
N	24,450	24,450	24,450

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual.

Table A10: Random-Effects Regressions for the Mediation of Being Married or Cohabited in the Effect of Education on Overall Health Status Including Control Variables

	Married or cohabited	At least good overall health	At least good overall health
Years in education	0.00317**	0.0151***	0.0150***
	(2.91)	(15.68)	(15.53)
Married or cohabited			0.0349***
			(6.87)
Socio-economic background (ref.: parents with low levels of education)			
Medium level of education	-0.0168*	0.00706	0.00760
	(-2.14)	(0.99)	(1.06)
Higher level of education	-0.0448***	0.0162*	0.0177*
	(-5.30)	(2.10)	(2.30)
Other degree	-0.0288**	-0.00391	-0.00302
	(-3.14)	(-0.48)	(-0.37)
Age group (ref.: 30-39)			
40-49	-0.0178***	-0.0720***	-0.0703***
	(-3.66)	(-13.52)	(-13.20)
50-60	-0.0246***	-0.156***	-0.154***
	(-4.47)	(-27.19)	(-26.79)
West Germany	-0.0195*	-0.0327***	-0.0315***
	(-2.35)	(-5.71)	(-5.50)
Gender (ref.: male)			
Female	-0.0542***	-0.0668***	-0.0646***
	(-10.12)	(-13.45)	(-13.00)
Migration background	0.139***	0.0452***	0.0409***
	(21.84)	(7.71)	(6.96)
Sample affiliation (ref.: general population sample)			
PASS welfare benefit recipients sample	-0.295***	-0.121***	-0.111***
	(-50.92)	(-22.08)	(-19.42)
Number of children	0.0570***	0.00404*	0.00114
	(29.72)	(2.30)	(0.63)
Survey wave (ref.: wave 1)			
Wave 2	-0.0135***	-0.0104	-0.00933
	(-5.30)	(-1.59)	(-1.42)
Wave 3	-0.0117***	-0.0311***	-0.0300***
	(-3.92)	(-4.67)	(-4.51)
Wave 4	-0.0107**	-0.0185**	-0.0177*
	(-2.92)	(-2.67)	(-2.56)
Wave 5	-0.00918*	-0.0171*	-0.0166*
	(-2.35)	(-2.56)	(-2.47)
Wave 6	-0.00692	-0.0301***	-0.0298***
	(-1.65)	(-4.44)	(-4.39)
Wave 7	-0.00609	-0.0712***	-0.0709***
	(-1.38)	(-10.28)	(-10.24)
Wave 8	-0.00814	-0.0478***	-0.0475***
	(-1.73)	(-6.75)	(-6.71)
Wave 9	-0.0107*	-0.0541***	-0.0538***
	(-2.17)	(-7.45)	(-7.40)
Wave 10	-0.0110*	-0.0617***	-0.0615***
	(-2.11)	(-8.36)	(-8.33)
Wave 11	-0.0130*	-0.0467***	-0.0464***
	(-2.39)	(-6.36)	(-6.33)
Wave 12	-0.0135*	-0.0577***	-0.0574***
	(-2.41)	(-7.65)	(-7.62)
Constant	0.754***	0.502***	0.476***
	(43.58)	(32.77)	(30.18)
Observations	85,881	85,881	85,881
N	24,450	24,450	24,450

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual.

Table A11: Random-Effects Regressions for the Mediation of the Number of Close Friends and Relatives outside the Household in the Effect of Education on Overall Health Status Including Control Variables

	Number of close friends and relatives outside the household (ln)	At least good overall health	At least good overall health
Years of education	0.0157***	0.0151***	0.0146***
	(11.12)	(15.68)	(15.20)
Number of close friends and relatives outside the household (ln)			0.0304***
			(10.76)
Socio-economic background (ref.: parents with low levels of education)			
Medium level of education	0.0346***	0.00706	0.00596
	(3.43)	(0.99)	(0.84)
Higher level of education	0.0405***	0.0162*	0.0148
	(3.68)	(2.10)	(1.93)
Other degree	-0.0296*	-0.00391	-0.00302
	(-2.36)	(-0.48)	(-0.37)
Age group (ref.: 30-39)			
40-49	-0.0320***	-0.0720***	-0.0712***
	(-4.68)	(-13.52)	(-13.39)
50-60	0.00177	-0.156***	-0.157***
	(0.23)	(-27.19)	(-27.35)
West Germany	-0.0458***	-0.0327***	-0.0313***
	(-5.60)	(-5.71)	(-5.46)
Gender (ref.: male)			
Female	-0.0566***	-0.0668***	-0.0651***
	(-7.78)	(-13.45)	(-13.15)
Migration background	0.0398***	0.0452***	0.0440***
	(4.52)	(7.71)	(7.52)
Sample affiliation (ref.: general population sample)			
PASS welfare benefit recipients sample	-0.0818***	-0.121***	-0.119***
	(-10.23)	(-22.08)	(-21.68)
Number of children	0.0168***	0.00404*	0.00354*
	(6.34)	(2.30)	(2.02)
Survey wave (ref.: wave 1)			
Wave 2	-0.0286***	-0.0104	-0.00950
	(-3.40)	(-1.59)	(-1.45)
Wave 3	-0.117***	-0.0311***	-0.0275***
	(-13.60)	(-4.67)	(-4.13)
Wave 4	-0.104***	-0.0185**	-0.0154*
	(-11.96)	(-2.67)	(-2.22)
Wave 5	-0.141***	-0.0171*	-0.0130
	(-16.30)	(-2.56)	(-1.94)
Wave 6	-0.136***	-0.0301***	-0.0262***
	(-15.56)	(-4.44)	(-3.85)
Wave 7	-0.159***	-0.0712***	-0.0665***
	(-18.15)	(-10.28)	(-9.59)
Wave 8	-0.152***	-0.0478***	-0.0433***
	(-17.15)	(-6.75)	(-6.11)
Wave 9	-0.135***	-0.0541***	-0.0501***
	(-14.89)	(-7.45)	(-6.89)
Wave 10	-0.145***	-0.0617***	-0.0574***
	(-15.86)	(-8.36)	(-7.77)
Wave 11	-0.144***	-0.0467***	-0.0426***
	(-15.77)	(-6.36)	(-5.80)
Wave 12	-0.147***	-0.0577***	-0.0534***
	(-15.86)	(-7.65)	(-7.07)
Constant	1.946***	0.502***	0.443***
	(87.14)	(32.77)	(27.39)
Observations	85,881	85,881	85,881
N	24,450	24,450	24,450

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual.

Table A12: Random-Effects Regressions for the Mediation of the Active Membership in a Voluntary Association in the Effect of Education on Overall Health Status Including Control Variables

	Active membership in a voluntary association	**At least good overall health**	**At least good overall health**
Years in education	0.0242***	0.0151***	0.0148***
	(24.11)	(15.68)	(15.21)
Active membership in a voluntary association			0.0149***
			(3.79)
Socio-economic background (ref.: parents with low levels of education)			
Middle level of education	0.0149	0.00706	0.00682
	(1.93)	(0.99)	(0.95)
Higher level of education	0.0338***	0.0162*	0.0157*
	(4.13)	(2.10)	(2.04)
Other degree	-0.0528***	-0.00391	-0.00313
	(-6.57)	(-0.48)	(-0.38)
Age group (ref.: 30-39)			
40-49	0.0170**	-0.0720***	-0.0723***
	(3.24)	(-13.52)	(-13.57)
50-60	0.0356***	-0.156***	-0.157***
	(6.13)	(-27.19)	(-27.29)
West Germany	0.0547***	-0.0327***	-0.0335***
	(8.89)	(-5.71)	(-5.85)
Gender (ref.: male)			
Female	-0.0591***	-0.0668***	-0.0659***
	(-11.37)	(-13.45)	(-13.27)
Migration background	-0.121***	0.0452***	0.0470***
	(-20.42)	(7.71)	(8.00)
Sample affiliation (ref.: general population sample)			
PASS welfare benefit recipients sample	-0.190***	-0.121***	-0.119***
	(-31.66)	(-22.08)	(-21.40)
Number of children	0.00217	0.00404*	0.00401*
	(1.25)	(2.30)	(2.28)
Survey wave (ref.: wave 1)			
Wave 2	-0.0135*	-0.0104	-0.0102
	(-2.44)	(-1.59)	(-1.56)
Wave 3	-0.00319	-0.0311***	-0.0311***
	(-0.56)	(-4.67)	(-4.66)
Wave 4	0.0220***	-0.0185**	-0.0188**
	(3.69)	(-2.67)	(-2.72)
Wave 5	0.0212***	-0.0171*	-0.0174**
	(3.56)	(-2.56)	(-2.60)
Wave 6	0.0276***	-0.0301***	-0.0305***
	(4.44)	(-4.44)	(-4.50)
Wave 7	0.0161*	-0.0712***	-0.0714***
	(2.54)	(-10.28)	(-10.31)
Wave 8	0.0222***	-0.0478***	-0.0481***
	(3.36)	(-6.75)	(-6.80)
Wave 9	0.0388***	-0.0541***	-0.0547***
	(5.79)	(-7.45)	(-7.52)
Wave 10	0.0274***	-0.0617***	-0.0621***
	(4.05)	(-8.36)	(-8.41)
Wave 11	-0.000561	-0.0467***	-0.0467***
	(-0.08)	(-6.36)	(-6.36)
Wave 12	0.0221**	-0.0577***	-0.0580***
	(3.10)	(-7.65)	(-7.69)
Constant	0.222***	0.502***	0.499***
	(14.06)	(32.77)	(32.53)
Observations	85,881	85,881	85,881
N	24,450	24,450	24,450

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual.

Table A13: Fixed-Effects Regression Models for the Effect of Social Relationships on Overall Health Status Including Control Variables

	At least good overall health	At least good overall health	At least good overall health	At least good overall health
Level of social integration	0.0013 (0.0026)			
Married or cohabited		-0.0123 (0.0096)		
Number of close friends and relatives outside the household (ln)			0.0140*** (0.0036)	
Membership in a voluntary association				0.0063 (0.0050)
Age group (ref.: 30-39)				
40-49	-0.0004 (0.0094)	-0.0004 (0.0094)	0.0001 (0.0094)	-0.0005 (0.0094)
50-60	-0.0114 (0.0131)	-0.0114 (0.0131)	-0.0112 (0.0131)	-0.0115 (0.0131)
West Germany	-0.0199 (0.0324)	-0.0186 (0.0324)	-0.0203 (0.0324)	-0.0195 (0.0324)
Number of children	-0.0138*** (0.0041)	-0.0133** (0.0041)	-0.0138*** (0.0041)	-0.0137*** (0.0041)
Survey wave (ref.: wave 1)				
Wave 2	-0.0180* (0.0072)	-0.0181* (0.0072)	-0.0177* (0.0072)	-0.0180* (0.0072)
Wave 3	-0.0433*** (0.0074)	-0.0434*** (0.0074)	-0.0416*** (0.0075)	-0.0433*** (0.0074)
Wave 4	-0.0354*** (0.0079)	-0.0355*** (0.0079)	-0.0339*** (0.0079)	-0.0356*** (0.0079)
Wave 5	-0.0452*** (0.0081)	-0.0454*** (0.0081)	-0.0430*** (0.0082)	-0.0454*** (0.0082)
Wave 6	-0.0615*** (0.0083)	-0.0616*** (0.0083)	-0.0594*** (0.0084)	-0.0618*** (0.0083)
Wave 7	-0.1108*** (0.0087)	-0.1110*** (0.0087)	-0.1085*** (0.0087)	-0.1110*** (0.0087)
Wave 8	-0.0924*** (0.0090)	-0.0926*** (0.0090)	-0.0901*** (0.0090)	-0.0926*** (0.0090)
Wave 9	-0.1076*** (0.0094)	-0.1077*** (0.0094)	-0.1055*** (0.0094)	-0.1079*** (0.0094)
Wave 10	-0.1228*** (0.0099)	-0.1230*** (0.0099)	-0.1206*** (0.0099)	-0.1230*** (0.0099)
Wave 11	-0.1173*** (0.0103)	-0.1176*** (0.0103)	-0.1150*** (0.0103)	-0.1174*** (0.0103)
Wave 12	-0.1417*** (0.0108)	-0.1420*** (0.0108)	-0.1394*** (0.0108)	-0.1419*** (0.0108)
Constant	0.5572*** (0.0264)	0.5678*** (0.0259)	0.5324*** (0.0264)	0.5583*** (0.0255)
Observations	85,881	85,881	85,881	85,881
N	24,450	24,450	24,450	24,450

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=24,450.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual.

Table A14: Random-Effects Regressions for the Mediation of the Emotional Support in the Effect of Education on Mental Health Including Control Variables

	Emotional support	At least good mental health	At least good mental health
Years of education	0.0072***	0.0072***	0.0067***
	(0.0010)	(0.0019)	(0.0019)
Emotional support			0.0658***
			(0.0199)
Socio-economic background (ref.: parents with low levels of education)			
Medium level of education	0.0065	-0.0063	-0.0067
	(0.0056)	(0.0134)	(0.0134)
Higher level of education	0.0067	-0.0118	-0.0122
	(0.0058)	(0.0148)	(0.0148)
Other degree	-0.0178	0.0005	0.0016
	(0.0092)	(0.0160)	(0.0159)
Age group (ref.: 30-39)			
40-49	-0.0322***	-0.0207	-0.0186
	(0.0049)	(0.0114)	(0.0114)
50-60	-0.0380***	-0.0260*	-0.0235
	(0.0055)	(0.0121)	(0.0121)
West Germany	-0.0023	-0.0364***	-0.0363***
	(0.0051)	(0.0109)	(0.0109)
Gender (ref.: male)			
Female	0.0301***	-0.1099***	-0.1119***
	(0.0046)	(0.0094)	(0.0094)
Migration background	-0.0602***	0.0150	0.0189
	(0.0072)	(0.0119)	(0.0120)
Sample affiliation (ref.: general population sample)			
PASS welfare benefit recipients sample	-0.0250***	-0.1069***	-0.1053***
	(0.0047)	(0.0101)	(0.0101)
Number of children	0.0005	0.0091*	0.0091*
	(0.0020)	(0.0037)	(0.0037)
Survey Wave (ref.: wave 5)			
Wave 3	-0.0141***	-0.0205**	-0.0195*
	(0.0036)	(0.0076)	(0.0076)
Constant	0.9018***	0.7217***	0.6624***
	(0.0154)	(0.0296)	(0.0348)
Observations	12,298	12,298	12,298
N	8,054	8,054	8,054

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=8,054, only individuals observed in wave 3 and 5.
Note: Clustered standard errors by individuals in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A15: Random-Effects Regressions for the Mediation of Work-Related Support in the Effect of Education on Mental Health Including Control Variables

	Work-related support	**At least good mental health**	**At least good mental health**
Years of education	0.0111***	0.0072***	0.0067***
	(0.0014)	(0.0019)	(0.0019)
Work-related support			0.0397**
			(0.0130)
Socio-economic background (ref.: parents with low levels of education)			
Medium level of education	0.0116	-0.0063	-0.0067
	(0.0090)	(0.0134)	(0.0134)
Higher level of education	0.0164	-0.0118	-0.0124
	(0.0098)	(0.0148)	(0.0148)
Other degree	-0.0408**	0.0005	0.0021
	(0.0131)	(0.0160)	(0.0159)
Age group (ref.: 30-39)			
40-49	-0.0488***	-0.0207	-0.0188
	(0.0074)	(0.0114)	(0.0114)
50-60	-0.1229***	-0.0260*	-0.0211
	(0.0087)	(0.0121)	(0.0121)
West Germany	0.0050	-0.0364***	-0.0366***
	(0.0080)	(0.0109)	(0.0109)
Gender (ref.: male)			
Female	0.0284***	-0.1099***	-0.1110***
	(0.0069)	(0.0094)	(0.0094)
Migration background	-0.1509***	0.0150	0.0210
	(0.0103)	(0.0119)	(0.0121)
Sample affiliation (ref.: general population sample)			
PASS welfare benefit recipients sample	-0.0355***	-0.1069***	-0.1055***
	(0.0074)	(0.0101)	(0.0101)
Number of children	-0.0056*	0.0091*	0.0094*
	(0.0029)	(0.0037)	(0.0037)
Survey Wave (ref.: wave 5)			
Wave 3	-0.0575***	-0.0205**	-0.0182*
	(0.0054)	(0.0076)	(0.0076)
Constant	0.8542***	0.7217***	0.6878***
	(0.0233)	(0.0296)	(0.0318)
Observations	12,298	12,298	12,298
N	8,054	8,054	8,054

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=8,054, only individuals observed in wave 3 and 5.
Note: Clustered standard errors by individuals in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A16: Random-Effects Regressions for the Mediation of Financial Support in the Effect of Education on Mental Health Including Control Variables

	Financial Support	At least good mental health	At least good mental health
Years of education	0.0269***	0.0072***	0.0050**
	(0.0016)	(0.0019)	(0.0019)
Financial Support			0.0803***
			(0.0107)
Socio-economic background (ref.: parents with low levels of education)			
Medium level of education	0.0373**	-0.0063	-0.0092
	(0.0115)	(0.0134)	(0.0134)
Higher level of education	0.0372**	-0.0118	-0.0147
	(0.0121)	(0.0148)	(0.0148)
Other degree	-0.0866***	0.0005	0.0073
	(0.0160)	(0.0160)	(0.0159)
Age group (ref.: 30-39)			
40-49	-0.0305**	-0.0207	-0.0182
	(0.0100)	(0.0114)	(0.0114)
50-60	-0.0303**	-0.0260*	-0.0234
	(0.0107)	(0.0121)	(0.0120)
West Germany	0.0308**	-0.0364***	-0.0389***
	(0.0101)	(0.0109)	(0.0109)
Gender (ref.: male)			
Female	0.0377***	-0.1099***	-0.1129***
	(0.0085)	(0.0094)	(0.0093)
Migration background	-0.0542***	0.0150	0.0193
	(0.0115)	(0.0119)	(0.0119)
BA sample	-0.1869***	-0.1069***	-0.0919***
	(0.0090)	(0.0101)	(0.0103)
Number of children	0.0005	0.0091*	0.0091*
	(0.0034)	(0.0037)	(0.0037)
Survey Wave (ref.: wave 5)			
Wave 3	-0.0580***	-0.0205**	-0.0158*
	(0.0062)	(0.0076)	(0.0076)
Constant	0.5357***	0.7217***	0.6786***
	(0.0266)	(0.0296)	(0.0302)
Observations	12,298	12,298	12,298
N	8,054	8,054	8,054

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=8,054, only individuals observed in wave 3 and 5.
Note: Clustered standard errors by individuals in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual.

Table A17: The Total, Direct and Indirect Effects of Education for Social Support

Mediator	**Total effect of education on mental health β_1**	**Direct effect of education on mental health β_2**	**Indirect Effect[1] $\beta_1 - \beta_2$**	**Proportion of the indirect effect on the total effect of education**
Emotional support	0.0072*** (0.0019)	0.0067*** (0.0019)	0.0005**	6.94%
Work-related support	0.0072*** (0.0019)	0.0067*** (0.0019)	0.0005**	6.94%
Financial support	0.0072*** (0.0019)	0.0050** (0.0019)	0.0022***	30,55%

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=8,054, only individuals observed in wave 3 and 5.
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual.
[1] Small differences in the calculation of the total effect based on the indirect and direct effects reported and the estimation results presented in column 1 are due to rounding errors.

Table A18: Fixed-Effects Regression Models for the Effect of Social Support on Mental Health Including Control Variables

	At least good mental health	**At least good mental health**	**At least good mental health**
Emotional Support	0.0097 (0.0336)		
Work-related support		0.0105 (0.0230)	
Financial support			0.0536** (0.0196)
Age group (ref.: 30-39)			
40-49	-0.0195 (0.0316)	-0.0191 (0.0316)	-0.0202 (0.0317)
50-60	-0.0440 (0.0449)	-0.0434 (0.0450)	-0.0470 (0.0450)
West Germany	0.2040 (0.1514)	0.2050 (0.1511)	0.2113 (0.1502)
Number of own children	0.0097 (0.0144)	0.0098 (0.0144)	0.0086 (0.0143)
Survey Wave (ref.: wave 5)			
Wave 3	-0.0273** (0.0092)	-0.0269** (0.0093)	-0.0248** (0.0093)
Constant	0.5155*** (0.1197)	0.5142*** (0.1170)	0.4817*** (0.1149)
Observations	12,298	12,298	12,298
N	8,054	8,054	8,054

Source: PASS, Welle 12 v1 (DOI: 10.5164/IAB.PASS-SUF0618.de.en.v1), own calculation; N=8,054, only individuals observed in wave 3 and 5
Note: Clustered standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, standard errors clustered by individual.

Chapter 4 – Revisiting the causal effect of education on health (Article 3)

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Status: Unsubmitted

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Abstract

We revisit the question whether schooling has a causal impact on individuals' subjective health, body measurements and health-related behavior. Using data from the National Educational Panel Study (NEPS) on German adults, we investigate the effects of expanding compulsory schooling between 1949 and 1969 in former West Germany. We extend previous studies by using novel information on the reform based on historical documents, and longitudinal data on individuals' educational trajectories to examine a more precise causal effect of the reform. We further investigate effect heterogeneity by replicating reform definition and operationalization used in previous research. Our results question the interpretation of a causal effect of education on different measurements of health and health-related behavior. Overall, our study highlights the importance of a precise implementation strategy and the operationalization of education.

1 Introduction and background

Socioeconomic differences in health and mortality are observable all over the world. A promising strategy to reduce existing inequalities could be to empower people to invest more in better health and reduce risky health behavior (Woolf et al., 2007). Since differences in morbidity, mortality, and health-related behavior are highly associated with educational attainment (for review see Furnée et al., 2008; Galama et al., 2018; Cawley and Ruhm, 2012), increasing people's education levels appears to be a key to enabling people to take better care of their health.

From a theoretical perspective, there is good reason to argue that education enhances individuals' health. Economic theory suggests positive effects of education on several health (related) outcomes, whereby it increases individuals' productive and allocative efficiency by fostering the ability to acquire (health-related) knowledge (Grossman, 2000). Higher productive efficiency might positively affect individuals' health, as it is accompanied by higher cognitive and non-cognitive skills for generating higher outputs with given resources. These skills acquired through education enhance individuals' productivity on the labor market, and increase performance on the non-market sector. Thus, the more highly educated have a greater capacity to produce monetary (income and wealth) and non-monetary resources contributing to better health outcomes (Ross and Wu, 1995; Link and Phelan, 1995). Moreover, higher productive efficiency is linked to higher health outcomes, because individuals are more likely to make optimal investments in their health over their life course, given their existing health stock and resources (Grossman, 2006). This complements the concept of allocative efficiency, which reflects individuals' ability to pick the right mixture of inputs to produce good health. With higher skill and knowledge levels, highly educated are more aware of healthy behavior or health-related problems, and are more likely to adopt positive health behavior and reduce negative behavior compared to the less educated (Grossman, 2006).

Empirical studies support these theoretical expectations (for reviews see Galama et al. 2018; Hamad et al., 2018; Cawley and Ruhm, 2012), yet there is a wide and ongoing discussion concerning whether the relationship between education and health is causal (e.g. Adams et al., 2003; Duke and Macmillan, 2016; Mazumder, 2008; Hamad et al., 2018). The correlation might well be spurious, with other relevant, unobserved factors, like cognitive skills levels, or background characteristics, determining health outcomes, so that education is endogenous in the education-health relationship. For instance, competent individuals might be more able to watch over and improve their health, as well as to acquire more education (Link et al., 2008). Good health could also be a primary condition for acquiring human capital, which, however, might also be initiated by confounding variables, like early health, parental social background, and resulting early life circumstances (Ben-Shlomo and Kuh, 2002).

To address this potential endogeneity of education in the education-health relationship caused by confounding variables, a large number of studies exploit exogenous variation using educational reforms all over the world (e.g. Dilmaghani, 2020; Janke et al., 2020; Braakmann, 2011; Albarrán et al., 2020; Makate and Makate, 2016). By employing quasi-experimental designs, they focus on causality in the relationship between education and, inter alia, health status, health-related behavior, and mortality. Results, however, differ substantially between these studies. While many studies indicate that education has positive effects on health, many others find no such causal relationship (for review see Hamad et al., 2018). Although the meta-analysis conducted by Hamad et al. (2018) highlights the beneficial effects of education on mortality, and on individuals' smoking or nutrition, high variation in the effects of education on a variety of health outcomes raises concern about the validity of previous results.

The observed inconsistencies in international research also apply to the German context, which is also our focus here. Except for the study by Braakmann (2010), all others applied instrumental variable techniques to identify the causal effect of education on health (Kemptner et al., 2011; Reinhold and Jürges, 2010; Jürges et al., 2011). Based on a two-stage estimation procedure, Kemptner et al. (2011), Reinhold and Jürges (2010) and Jürges et al. (2011) use the variation in education caused by political reforms as instruments to estimate causal effects on health. However, results differ substantially. The exogenous variation in education caused by the abolition of school fees shows no observed effect on the health status of the individual, nor does it affect smoking behavior or body weight (Reinhold and Jürges, 2010). In contrast, deploying the increasing number of upper secondary schools from 1960 to 1979, and the expansion of compulsory schooling between 1949 and 1969 as an instrument for education, shows effects preventing detrimental health behavior and encouraging general health (Kemptner et al., 2011; Jürges et al., 2011).

This observed heterogeneity in the effect of education on health might come down to methodological limitations. First, referring to Reinhold and Jürges (2010), weak identification of the effect of a reform on education might result in skewed standard errors in estimating the effect of education on health, because estimated variance in education is too small (Murray, 2006). Second, in the case of Jürges et al. (2011), implausibly high estimates in predictions of educational variance induced by the reform raise questions about consistency and the correct identification of the treatment effect in the IV-estimation. Finally, according to Kemptner et al. (2011), the parallel implementations of other educational reforms, like the shortened school years in 1966/1967, might bias the estimated causal effect of education on health, due to introduced endogeneity of education in the education-health equation (Kemptner et al., 2011; Angrist and Pischke, 2009). Moreover, insufficient detailed knowledge of the reform under study could lead to problems in applying school reforms as instruments. For example, new information on the extension of compulsory schooling points to limitations in the implementation strategy Kemptner et al. 2011 utilized (Helbig and Nikolai, 2015; Cygan-Rehm, 2018).

Besides these methodological concerns, prior studies also show data limitations, which might cause attenuation bias. First, the data used - from either the German Socio-economic Panel (SOEP) or the German Microcensus - does not provide detailed information about individuals' years of schooling. Previous studies thus used the highest secondary school qualification, average time spent in school to obtain a particular qualification, the current state of residence of respondents, and considered different compulsory schooling reforms to estimate individuals' years of schooling (Kemptner et al., 2011; Reinhold and Jürges, 2010; Jürges et al., 2011). This might be problematic firstly because the direct effect of political reforms on years of education is strong by definition if it is part of the calculation of an individuals' years of schooling (Kemptner et al., 2011). Next, if a student repeated a class, or obtained the highest secondary school qualification later in life, this leads to skewed measurement, because the actual time spent in school does not match the calculated years of schooling. Second, neither SOEP nor Microcensus provide detailed information for the state in which respondents were schooled. All previous studies have therefore used an individual's current state of residence as a proxy for the state in which they were schooled, thereby assuming respondents did not move after graduation from school. This is problematic for the definition of the treatment and control group: If an individual attended school in another federal state, it is unclear whether the individual was affected by the reform or not, which leads to problems of misclassification (Kramer and Tamm, 2018; Margaryan et al., 2019).

We address such limitations, and contribute to the existing literature by using data from the German National Educational Panel Study (NEPS). The NEPS offers detailed information on individuals' biographies, and provides reliable data on educational trajectories, which we use to address the aforementioned weaknesses. We follow prior studies (e.g. Kemptner et al., 2011), and exploit exogenous variation in compulsory schooling as instrument for estimating the effect of education on health, and health-related behavior. NEPS data, however, allow to use starting and ending dates of schooling episodes, school type attended, as well as information about both federal state and municipality where individuals' attended school. We can therefore identify exogenous changes in education much more precisely than previous studies, and determine correctly, whether individuals were affected by the compulsory schooling reform. As health outcomes, we look at subjective health status, body mass index, overweight and obesity, smoking, alcohol consumption, and physical activity. Whilst we find positive effects for alcohol consumption, we find no evidence for causal effects of education, as triggered by the reform, on individuals' long-term health and health-related behavior. We address assumptions about the reform implementation and concerns of the validity of the instrument used in prior studies for robustness checks. These additional analyses confirm our findings, and further highlight the impact of unobserved heterogeneity.

2 The West German school system and the schooling reforms

In Germany, the federal states are responsible for funding the school system and for its content and structure. The main features of the education system, however, have in general been identical since the mid of 20th century. Children start compulsory schooling around the age of six. Tracking into lower, middle and academic secondary schooling paths occurs at about age ten (for detailed information see KMK, 2019). Prior to World War II, compulsory schooling ended after eight years in most federal states, but after the war, the West German schooling system, which we focus on here, experienced changes with different interventions taking place to adjust for lack of training and employment opportunities (Helbig and Nikolai, 2015). We look at the period between 1949 and 1969, when two major changes occurred: the extension of compulsory schooling from eight to nine years (hereafter C9 reform) and the shift of the beginning of the school year from spring to autumn, as arranged in the "Hamburger Abkommen" of 1964 (Helbig and Nikolai, 2015).

Table 1: Implementation of the C9 Reform

Federal State	Our study	Pischke and von Wachter (2005; 2008) Kemptner et al. (2011)
Bremen	before 1949/50	1958
Hamburg	before 1949/50	1949
West Berlin	before 1949/50	-
Schleswig-Holstein	before 1949/50	1956
Lower Saxony*	1962/63	1962
Hesse (urban municipalities)**	1966 (1962/63)	1967
North Rhine-Westphalia	1966	1967
Rhineland-Palatinate	1966	1967
Saarland***	1966	1964
Baden-Wuerttemberg	1965/66	1967
Bavaria	1968/69	1969

* Lower Saxony gradually implemented the reform in 1954/55 and 1962/63.

** In Hesse, the reform was first implemented in urban municipalities in 1962/63.

*** Saarland gradually implemented the reform from 1958/59 to 1966.

We exploit the exogenous variation that was induced by the C9 reform. Compared to earlier studies, we follow - with one exception - Helbig and Nikolai (2015) for the description of the reform in the federal states, which is based on novel, considerably better documented, systematized historical information (see Table 1). The expansion was first implemented in 1949 in northern Germany. Middle and southern West Germany followed between 1962 and 1967. Compared to Kemptner et al. (2011), we assume earlier reform implementation dates for Bremen, Schleswig-Holstein, Baden-Württemberg, and Hesse, but a later point in time for Saarland. We, however, depart from Helbig and Nikolai (2015) in one case: In Bavaria, they date the reform to 1969/ 1970, but our data strongly suggests that it was implemented in the school year 1968/69, which is in line with Pischke and von Wachter (2005) and Cygan-Rehm (2018).

Some further specifics of the C9 reform are relevant. First, because of a lack of teachers, a few federal states implemented a transitional arrangement. In Hesse, Lower Saxony and Saarland the C9-reform was implemented gradually between 1954 and 1966 (Helbig and Nikolai, 2015). Second, partly overlapping with the C9 reform, all federal states except for Bavaria, where the school year already used to start in autumn, shifted the start of the school year from spring to autumn in 1966/1967. To do so, most of federal states introduced two short-school years, from April to November 1966, and from December 1966 to June 1967. Only Hamburg and West Berlin decided to implement one long-school year from April 1966 to August 1967.

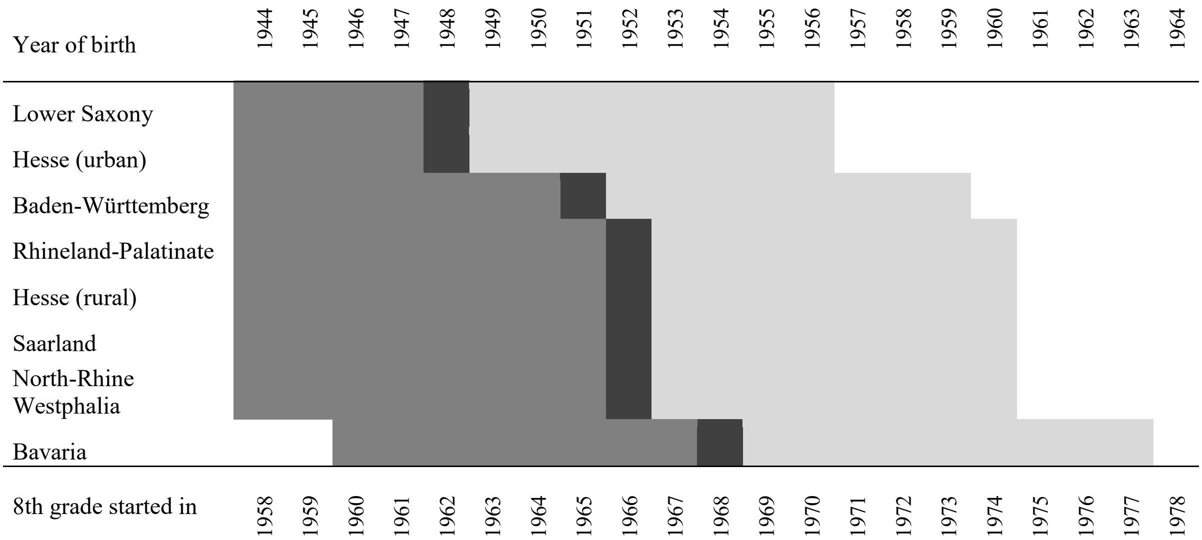
However, while transitional arrangements can be addressed in the implementation strategy, short-school years might be problematic for using compulsory schooling as an instrument, because the shortened school years increased the risk of students repeating classes (Pischke, 2007). Grade repetition might be endogenous in the education-health estimation due to unobserved factors. Individuals with lower cognitive skills might, for instance, have had difficulty acquiring knowledge as fast as their classmates did, and may have had a higher likelihood of repeating a class. Since the two reforms coincide in some states, the effect of the C9 reform could be underestimated if the potential effects of the second reform, which changed the academic year starting date, are not considered. We address this in our robustness checks by excluding individuals who repeated at least one class.

3 Data

We use data from the adult cohort of the National Educational Panel Study (NEPS) in Germany. The data encompasses 17,140 individuals born between 1944 and 1986, and provides detailed information on individual educational biographies and information about educational and professional careers, respondents' life circumstances, and different measurements of educational outcomes (Leibniz institute for educational trajectories, 2017; Blossfeld et al., 2011). We employ health indicators that were measured in 2011/2012 (wave 4) and in 2014/2015 (wave 7).

Following Cygan-Rehm and Maeder (2013), we avoid large age differences by restricting our sample to individuals who attended the 8th grade between nine years before, and nine years after the C9 reform in the respective federal state (see Figure 1).

Figure 1: Sample Definition by each Federal State and Time of the Reform (Black)



Source: Helbig and Nikolai (2015); Cygan-Rehm (2018); Cygan-Rehm and Maeder (2013); own illustration.

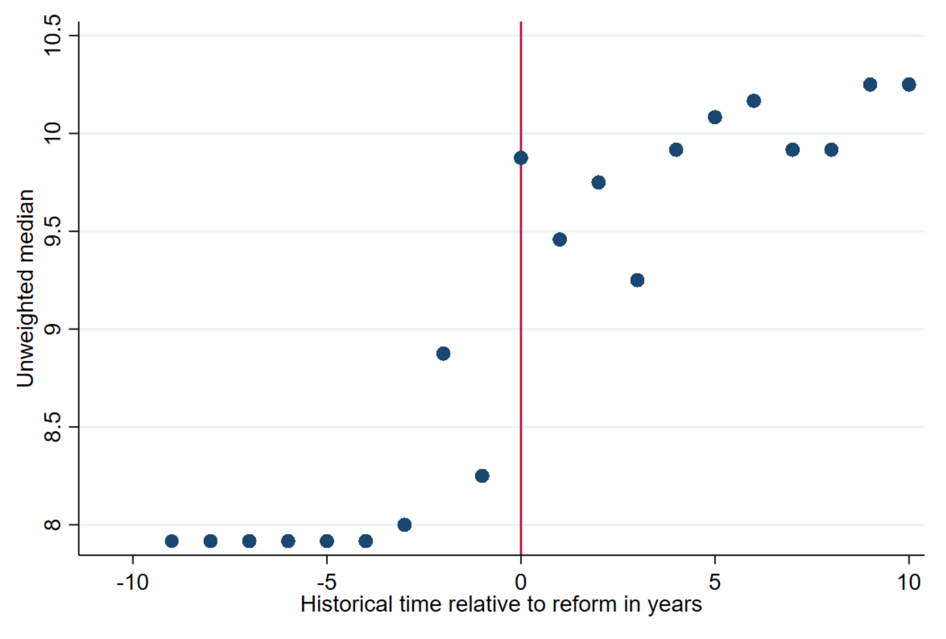
Note: Federal states with variation in compulsory schooling in our sample. Schleswig-Holstein, Hamburg, Bremen and West-Berlin are exluded, because the reform took place before 1950.

We impose further restrictions on our sample: (1) we only consider individuals that attended school in grade eight in one of the federal states with reform-based changes in compulsory education in West Germany between 1960 and 1970; (2) we only include individuals born in Germany, to avoid systematic differences in compulsory schooling between natives and migrants; (3) we exclude individuals with years of schooling below the 1st, or above the 99th percentile, to reduce potential measurement error bias; (4) we only include cases that do not have missing values in variables related to health, education and residence; (5) we exclude observations from federal states which implemented the reform in 1949/1950, for which we do not observe any variation in compulsory schooling, i.e. the federal states Bremen, Hamburg, Schleswig-Holstein, and West-Berlin. Our analysis sample contains 2,853 individuals (detailed information on data preparation available upon request).

Reform-related measures We use longitudinal information on respondents' educational trajectories to estimate the causal effect of education on health-related outcomes. To calculate respondents' actual duration of years of schooling, we use starting and ending dates of schooling episodes in primary and secondary schools. We consider typical pathways in the general education system, and alternative routes to educational certificates, including general education in vocational tracks. To identify individuals treated by the C9 reform, we use geographical information, i.e. the federal state and municipality in which respondents were schooled, and individuals' grade level at the time of the reform. For our definition of grade level, we consider individuals' class repetitions until grade nine. An individual is defined to be affected by the reform studied, if she or he was at school and had not yet completed grade 9 and left school after the state-specific cut off point shown in Table 1. For Saarland and Lower Saxony, we are not able to retrace the implementation of the reform in detail. We therefore assume that all individuals were affected by the reform from 1962/63 onwards for Lower Saxony, and from 1966 in Saarland. Sensitivity analyses indicate that the definition of the time of the reform in Lower Saxony and Saarland does not bias the main results (see Table A1 of the Appendix).

Figure 2 shows the weighted median of years of schooling for each school-leaving cohort nine years before and after the extension of compulsory schooling. We use cross-sectional sample weights to adjust for nonresponse and to improve the representativeness of our sample. As expected, we observe a clear level shift in years of schooling at the time of the reform. We additionally observe an increase in years of schooling after the reform, which indicates that individuals stayed longer in school, after the C9 reform was implemented. This is plausible because the expansion of compulsory schooling lowered the individual's relative costs of choosing the intermediate, or potentially the academic track instead of leaving schooling after nine years (Helbig and Nikolai, 2015). These effects do, however, not limit the validity of the instrument since the overall track choice was not directly affected by the reform (Pischke and Wachter, 2005; Cygan-Rehm, 2018).

Figure 2: Weighted Median of Years of Schooling of School Leaving Cohorts Before and After the Reform



Source: NEPS (2018); own calculation.

Health-related outcomes Our dependent measurements include the current health status and health-related behavior. We measure current health status using self-rated health. Respondents were asked to rate their health as "very good", "good", "average", "poor", or "very poor". In line with previous research, we recode the self-rated health measure as a binary variable specifying poor health (1) if one reports "poor" to "very poor" health (e.g. Brunello et al., 2016). As an indicator for current physical fitness, and as predictor for present as well as future illnesses (Pate et al., 2012), we use individuals' body mass index (BMI), calculated using self-reported weight and height. We in addition generate two binary variables for being overweight (BMI>=25) and being obese (BMI>=30), following the categorization of the World Health Organization (WHO, 2018a).

We approximate health-related behavior using information on smoking behavior, alcohol consumption and physical activity. We in particular use dummy variables, for current smoking, and having quit smoking. For alcohol consumption, we distinguish between regular (1) and non-regular drinkers (0) to identify individuals who drink alcohol at least twice a month. We further differentiate between heavy (1) and light (0) drinkers, classifying individuals as heavy drinkers, if they drink more than six standard alcoholic drinks (333ml beer, 125ml wine or 40ml liquor) per day of consumption (WHO, 2018b). For individuals' physical activity levels, we use information on respondents' frequency of sporting activity in the last three months prior to the interview, and the time spent doing physical activity. We follow recommendations of the WHO for adults and elderly, and define people as being physically active, if they undertook some physical activity in the last three months for more than two hours per week (WHO, 2018c).

Descriptive statistics Table 2 provides descriptive statistics for the full sample, and for the treatment and the control group. 49 percent of the sample are female, and the average age at the time of the interview is about 62. Individuals in the control group are on average five years older, while respondents in the treatment group are about eight years younger. We observe a slightly lower share of females in the control group, and the difference in years of schooling between the treatment and the control group is, on average, about one year.

Regarding health measures, only eight percent of the sample report a poor or very poor health status, and there is no statistical difference between the treatment and the control group. We observe group differences in respondents' physical condition (BMI, being overweight or being obese), smoking behavior and alcohol consumption. Individuals in the control group are more likely to be overweight (61% vs. 57%), obese (21% vs. 16%), are less likely to smoke (20% vs. 30%), and are more likely to have quitted smoking (68% vs. 54%). Individuals affected by the C9 reform tend to report regular drinking more frequently. However, descriptive results for heavy drinking and physical activity do not statistically differ between the treatment and the control group.

Table 2: Descriptive Statistics

	Sample Mean		**Control Group**		**Treatment Group**		**Δ**	
	mean	**sd**	**mean**	**sd**	**mean**	**sd**		
Age	61.87	(5.07)	67.09	(2.96)	58.89	(3.3)	-8.20	***
Female	0.49	(.5)	0.46	(.5)	0.50	(.5)	0.04	***
Years of schooling	10.36	(1.98)	9.77	(2.08)	10.69	(1.83)	0.92	***
Poor health	0.08	(.27)	0.08	(.27)	0.08	(.27)	0.00	
Body mass index	26.37	(4.44)	26.69	(4.38)	26.19	(4.47)	-0.50	**
Being overweight	0.59	(.49)	0.61	(.49)	0.57	(.49)	-0.04	*
Being obese	0.18	(.38)	0.21	(.41)	0.16	(.37)	-0.05	***
Smokes currently	0.26	(.44)	0.20	(.4)	0.30	(.46)	0.10	***
Quit smoking[1)]	0.59	(.49)	0.68	(.47)	0.54	(.5)	-0.14	***
Regular drinking	0.72	(.45)	0.73	(.45)	0.71	(.45)	-0.02	*
Heavy drinking[2)]	0.01	(.09)	0.01	(.09)	0.01	(.08)	0.00	
Being physically active	0.40	(.49)	0.40	(.49)	0.40	(.49)	0.00	

Source: NEPS (2018); N= 2,853; own calculations; standard deviations in parentheses.

1) N=1,837; sample, excluding individuals who never smoked
2) N= 2,632; sample excluding individuals who never drink alcohol

4 Estimation strategy

We first estimate the associations between education and health-related outcomes by OLS regression models. We regress individuals' *health* and *health-related behavior* on *years of schooling* and control for age-specific health effects by including *age* and *age squared*, as well as for *gender*, *survey wave*, *federal state*, and *cohort-, time- and state-specific trends*, following Kemptner et al. (2011). We further control for *cohort-specific age effects* to account for differences in education-based age trajectories in health across cohorts (Delaruelle et al., 2015). However, as we cannot account for cognitive skills or other important background characteristics, OLS regression results might be biased through confounding variables and self-selection into school tracks.

We address the potential endogeneity, and employ a two-stage least square, instrumental variable estimator (IV) using the exogenous variation in education induced by the C9 reform. We estimate *years of schooling* based on the C9 reform, and, similar to OLS regression, control for *age*, *age squared*, *gender*, *survey wave*, *federal state*, *cohort- and state-cohort specific trends* and *cohort-specific age effects*. In the second stage, we use the predicted years of schooling from the first stage regression to estimate the causal effect of education on our health measurements, conditional on the same controls as in the first stage. In both the OLS and IV-regression, we follow Cygan-Rehm (2018) and Pischke and Wachter (2005) and use clustered standard errors on federal state and year of birth level.

We validate the quality of the C9 reform as instrument and run different statistical tests as suggested by Stock and Yogo (2005) and Baum et al. (2007). For robustness checks, we first exclude individuals in higher secondary school tracks, and individuals who repeated at least one class. Secondly, we address the differences in the definitions of the reform years across the federal states between our study and that of Kemptner et al. (2011) by replicating their reform setting and operationalization.

5 Results

Table 3 provides results for OLS and IV estimations. The findings from OLS demonstrate strong statistical associations between schooling and health, as well as health-related behavior: In particular, schooling is negatively associated with individuals' propensity of reporting *poor* *health*, their *BMI*, their propensity of *being overweight*, or *obese*, of *currently smoking,* and *heavily drinking*. Complementing these overall positive education-health patterns, we see that schooling is positively related to individuals' propensity of *quitting smoking* and of *being physically active*. We however observe a statistical association between schooling and *regular drinking*.

The first stage estimates of the IV regressions indicate (Table 3, column 3) that after the C9 reform, individuals attended school for about six months longer than individuals who left school prior to the reform. In all models, the beta coefficients are all statistically significant at the 1 percent level, and indicate no weakness of the instrument. Compared to previous studies, the coefficients, however, are somewhat smaller, possibly because of the differences in the implementation strategy, which we address in our robustness checks. Second stage results are given in Table 3, column 4. With one exception, none of the coefficients are statistically different from zero. This means that despite positive correlations between education and individuals' health and health-related behavior, there is no (convincing) causal relationship. *Regular drinking* behavior is the exception. The result suggests that when years of schooling increase as result of the reform, the predicted probability of drinking alcohol more than once per month increases.

Table 3: OLS and IV Results: Full Sample

	OLS	IV	
		First-stage	Second-stage
Poor health	-0.010***	0.492***	0.016
	(0.0026)	(0.1294)	(0.0434)
		14.483	
Body mass index	-0.308***	0.492***	0.420
	(0.0482)	(0.1294)	(0.7772)
		14.483	
Being overweight	-0.030***	0.492***	-0.027
	(0.0053)	(0.1294)	(0.0661)
		14.483	
Being obese	-0.021***	0.492***	-0.036
	(0.0040)	(0.1294)	(0.0725)
		14.483	
Smoking currently	-0.019***	0.492***	0.033
	(0.0041)	(0.1294)	(0.0791)
		14.483	
Quit smoking 1)	0.017***	0.697***	0.015
	(0.0051)	(0.1799)	(0.0741)
		15.030	
Regular drinking	0.033***	0.492***	0.175**
	(0.0043)	(0.1294)	(0.0802)
		14.483	
Heavy drinking 2)	-0.002**	0.497***	-0.021
	(0.0008)	(0.1396)	(0.0145)
		12.663	
Being physically active	0.018***	0.492***	-0.074
	(0.0048)	(0.1294)	(0.0796)
		14.483	

Source: NEPS (2018); N= 2,853; own calculations.
1) N=1,837; sample, excluding individuals who never smoked
2) N= 2,628; sample excluding individuals who never drink alcohol

Note: Clustered standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Kleibergen Paap Wald F-Statistic in italics; controls OLS: μ_{state}, $\delta_{state} * cohort$ and ϑ_{cohort} *age, age, age², panel wave, gender; controls IV: μ_{state}, $\delta_{state} * cohort$, and ϑ_{cohort} *age, age, age²; standard errors are clustered for cohorts*state; in the IV-regression some controls are partialled out to adjust for small sample sizes.

6 Robustness checks

To test the robustness of our results, we run additional analyses to check the validity of the instrument. As a first concern, one may question the homogeneity of the effect (Morgan, 2002; Angrist et al., 1996). Because compulsory schooling in Germany directly affects the years of schooling in the lowest educational track only, the so-called monotonicity-assumption might be violated. However, if individuals that attended the lower track are systematically different before and after the reform, restricting the sample only to individuals who attended the lower secondary school track may then be problematic. As Cygan-Rehm (2018) illustrated in her analysis, the distributions of individuals who acquired the lowest and the middle secondary school degree differ significantly between these periods. This indicates an effect of the reform on track choice in the lower and middle secondary track. We therefore rerun our analyses excluding individuals that attended the upper secondary track, who most likely do not comply to the reform. Results indicate that the effect of the reform on years of schooling is smaller than in the full sample, with a weak instrument likely because of reduced reform effects and smaller sample size (see Table 4, estimations A). Although the first-stage indicates a limited statistical power of the estimation model, second-stage results are only slightly different compared to the full sample. Similar to the full sample, estimates indicate no causal effects of education on reporting poor health, BMI, being overweight, being obese, smoking behavior, physical activity and heavy drinking. In contrast to our main results, the effect of years of schooling on regular drinking is no longer statistically significant.

A second concern refers to the exclusion restriction. The expansion of compulsory schooling might be endogenous if the effect of the reform is correlated with individuals' background characteristics, which are known to confound the education-health relationship. While there is good reason to assume that, except for included covariates, the expansion of compulsory schooling is only linked to health via the resulting increase in individuals' education levels, the parallel introduction of short school years in some federal states may introduce confounding factors (Kemptner et al., 2011). While Kemptner et al. (2011) note that their results do not seem very sensitive for the simultaneous reform, increased repetition rates in schools during this period might have affected their results. We therefore exclude individuals who repeated at least one class.

Table 4: OLS and IV Results for Robustness Checks

	A: Excluding individuals in the upper secondary school track			B: Excluding individuals who repeated one class or more		
	OLS	**IV**		**OLS**	**IV**	
		First-Stage	**Second Stage**		**First-stage**	**Second-stage**
Poor health	-0.010***	0.297**	0.017	-0.012***	0.328**	0.02
	(0.0039)	(0.1337)	(0.0955)	(0.003)	(0.1438)	(0.0909)
		4.945			*5.192*	
Body mass index	-0.219***	0.297**	0.526	-0.362***	0.328**	0.737
	(0.0782)	(0.1337)	(1.484)	(0.0577)	(0.1438)	(1.3249)
		4.945			*5.192*	
Being overweight	-0.019**	0.297**	-0.093	-0.035***	0.328**	-0.05
	(0.0081)	(0.1337)	(0.1347)	(0.0064)	(0.1438)	(0.0939)
		4.945			*5.192*	
Being obese	-0.013**	0.297**	-0.099	-0.021***	0.328**	-0.039
	(0.0066)	(0.1337)	(0.1501)	(0.0044)	(0.1438)	(0.1125)
		4.945			*5.192*	
Smoking currently	-0.025***	0.297**	0.015	-0.022***	0.328**	0.005
	(0.0062)	(0.1337)	(0.12)	(0.005)	(0.1438)	(0.1302)
		4.945			*5.192*	
Quit smoking 1)	0.027***	0.402***	-0.016	0.016**	0.529***	0.039
	(0.0082)	(0.1526)	(0.1283)	(0.007)	(0.1934)	(0.1041)
		6.939			*7.498*	
Regular drinking	0.030***	0.297**	0.231	0.036***	0.328**	0.267*
	(0.006)	(0.1337)	(0.1593)	(0.0051)	(0.1438)	(0.1396)
		4.945			*5.192*	
Heavy drinking 2)	-0.002	0.332**	-0.039	-0.002**	0.392**	-0.03
	(0.0013)	(0.1523)	(0.0309)	(0.0008)	(0.1549)	(0.0241)
		4.748			*6.416*	
Being physically active	0.026***	0.297**	-0.353*	0.025***	0.328**	-0.13
	(0.0079)	(0.1337)	(0.2118)	(0.0063)	(0.1438)	(0.135)
		4.945			*5.192*	

Source: NEPS (2018), A: N=2,021; B: N=2,209; own calculations.
1) A: N=1,316; B: N=1,379; sample, excluding individuals who have never smoked
2) A: N= 2,628; B: N= 2,040; sample excluding individuals who never drink alcohol

Note: Clustered standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Kleibergen Paap Wald F-Statistic in italics; controls OLS: μ_{state}, $\delta_{state} * cohort$ and ϑ_{cohort} *age, age, age², panel wave, gender; controls IV: μ_{state}, $\delta_{state} * cohort$, and ϑ_{cohort} *age, age, age²; standard errors are clustered for cohorts*state; in the IV-regression some controls are partialled out to adjust for small sample sizes.

The results presented in Table 4, estimations B show important changes in the first stage regressions. Restricting the sample only to individuals without class repetition significantly decreases the effect of the C9 reform, and the test statistics indicate a very weak instrument, possibly because of smaller variation in years of schooling. Second-stage results, however, support our main findings for most of the outcomes indicating no causal effects of years of schooling on health and health-related behavior. Yet, we again see a statistically significant effect of education on drinking alcohol at least once a month, and the coefficient is now larger.

In a last sensitivity analysis, we address the differences in the definition of the reform implementation between our study and that of Kemptner et al. (2011) that results from less precise information and data limitations. For that purpose, we replicate their study in four steps. First, we replace our cut-off points with those used by Kemptner et al. (2011). Second, we assign individuals to treatment or control group according to their year of birth, instead of the biographical NEPS information on schooling episodes and the time of the attendance in grade 8. Third, we replace 'years of schooling' with 'approximated years of schooling', deducted from the respondents' highest obtained school-leaving certificate. Following previous studies, we assume eight years for each individual attending school before the reform, and nine years otherwise for individuals that attended school in lower secondary track. For individuals that attended the middle and higher secondary track, we assume 10 and 13 years, respectively. We finally use state of residence instead of state of schooling to define if an individual was affected by changes in compulsory schooling in a specific federal state or not.

After changing the respective cut-off points, first stage regression results (see Table 5, Model 1) are in line with our findings presented before. The coefficients of the C9 reform on years of schooling, however, are slightly smaller. Regarding the second stage results, we see some substantial increases in effect sizes for reporting *poor health*, *being overweight* and *being obese*, but a smaller effect size for *quitting smoking*. However, except for *regular drinking,* large standard errors do not support any statistically significant effects of years of schooling.

Using individuals' 'birth year 'to identify the reform effects results in larger coefficients in the first-stage regressions, and a few changes in the second-stage regressions (see Table 5, Model 2). In particular, whereas we find almost no causal effect of schooling on health in the regressions as given in Table 3, we now see that schooling reduces the likelihood of being overweight and heavy drinking. The patterns for alcohol consumption also change: education now lowers individuals' propensity of *heavy drinking*, while the effect of years of schooling on *regular drinking* decreases in size and is no longer statistically significant.

Model 3 reports results after replacing years of schooling by the approximation deducted from the individual's highest educational certificate obtained in life. Second-stage results do not differ compared to Model 2, but the first-stage, i.e. the effect of the reform on years of education increases substantially in size. Results of the complete replication are given in Model 4. Using 'current state of residence' instead of 'state of schooling' for assigning individuals either to treatment or control, results indicate that schooling has no causal effect on individuals' health or health-related behavior.

We cannot directly compare our estimate to those of Kempter et al. (2011), because they provide estimates separately by gender. Our replication results, however, highlight notable differences compared to our main analysis, and indicate similarities with their study. Thus, the replication with NEPS data indicates a high level of sensitivity to the operationalization of the C9 reform and years of schooling. First, assigning individuals to treatment or control group based on birth year seems to be problematic, because this approach assumes educational trajectories to be linear and congruent for all individuals, but this is often not the case. For instance, by using year of birth as identification variable, we assume that all individuals started school in the year of their sixth birthday. However, due to state-specific variation, school start ages vary depending on children's months of birth, and individuals' scholastic ability. This leads to variation in the date of school entry. Moreover, calculating years of schooling using individuals' highest educational certificate attained may bias the effect of the reform on years of schooling.

The main reason for this is that different lengths in school years are not taken into account. The approximation of years of schooling using the highest educational certificate obtained is representative of the level of knowledge and skills attained, but not necessarily of the time invested in education. Thus, different operationalization of years of schooling may have different effects for results on individuals' health and health-related behavior: the actual time spent in school will affect the degree to which individuals' have been exposed to school socialization processes, which may shape individuals' (health related) behaviors, values, and norms differently.

Table 5: Estimation Results for Replication of the Implementation Strategy of Pischke and Wachter (2005; 2008) and Kemptner et al. (2011)

		Model 1	**Model 2**	**Model 3**	**Model 4**
Poor health	*First stage*	0.440***	0.696***	0.889***	0.805***
		(0.1389)	(0.1814)	(0.1761)	(0.1480)
		10.048	*14.704*	*25.480*	*29.558*
	Second stage	0.032	0.043	0.033	0.039
		(0.0506)	(0.0331)	(0.0252)	(0.0272)
Body mass index	*First stage*	0.440***	0.696***	0.889***	0.805***
		(0.1389)	(0.1814)	(0.1761)	(0.1480)
		10.048	*14.704*	*25.480*	*29.558*
	Second stage	0.019	-0.726	-0.569	-0.320
		(0.9668)	(0.4869)	(0.3655)	(0.3056)
Being overweight	*First stage*	0.440***	0.696***	0.889***	0.805***
		(0.1389)	(0.1814)	(0.1761)	(0.1480)
		10.048	*14.704*	*25.480*	*29.558*
	Second stage	-0.106	-0.142*	-0.111*	-0.054
		(0.0804)	(0.0791)	(0.0581)	(0.0473)
Being obese	*First stage*	0.440***	0.696***	0.889***	0.805***
		(0.1389)	(0.1814)	(0.1761)	(0.1480)
		10.048	*14.704*	*25.480*	*29.558*
	Second stage	-0.111	-0.061	-0.048	-0.044
		(0.0895)	(0.0469)	(0.0350)	(0.0310)
Reform definition ...					
... based on education trajectories		X			
... based on year of birth			X	X	X
Assigned years of schooling				X	X
Using current state of residence as proxy					X

Source: NEPS (2018), N=2,781; own calculations.

1) N=1,783; sample, excluding individuals who never smoked
2) N= 2,572; sample excluding individuals who never drink alcohol

Note: Clustered standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Kleibergen Paap Wald F-Statistic in italics; controls OLS: μ_{state}, $\delta_{state} * cohort$ and ϑ_{cohort} *age, age, age², panel wave, gender; controls IV: μ_{state}, $\delta_{state} * cohort$, and ϑ_{cohort} *age, age, age²; standard errors are clustered for cohorts*state. There is a smaller sample size compared to the estimation presented in Table 3 because of respondents who did move from regions of the former BRD to a federal state of the former GDR; In the IV-regression, some controls are partialled out to adjust for small sample sizes.

Table 5: Estimation Results for Replication of the Implementation Strategy of Pischke and Wachter (2005; 2008) and Kemptner et al. (2011) (continued)

		Model 1	Model 2	Model 3	Model 4
Smokes currently	*First stage*	0.440***	0.696***	0.889***	0.805***
		(0.1389)	(0.1814)	(0.1761)	(0.1480)
		10.048	*14.704*	*25.480*	*29.558*
	Second stage	0.018	0.029	0.023	0.031
		(0.0806)	(0.0515)	(0.0399)	(0.0419)
Quit smoking[1)]	*First stage*	0.440***	0.927***	1.136***	1.054***
		(0.1389)	(0.2142)	(0.1997)	(0.1922)
		12.133	*18.732*	*32.372*	*30.045*
	Second stage	-0.005	-0.017	-0.014	-0.015
		(0.0825)	(0.0545)	(0.0441)	(0.0443)
Regular drinking	*First stage*	0.440***	0.696***	0.889***	0.805***
		(0.1389)	(0.1814)	(0.1761)	(0.1480)
		10.048	*14.704*	*25.480*	*29.558*
	Second stage	0.152*	0.086	0.068	0.077
		(0.0906)	(0.0653)	(0.0488)	(0.0577)
Heavy drinking [2)]	*First stage*	0.440***	0.685***	0.808***	0.744***
		(0.1389)	(0.1885)	(0.1959)	(0.1669)
		7.582	*13.212*	*17.011*	*19.847*
	Second stage	-0.028	-0.021*	-0.018*	-0.007
		(0.0188)	(0.0114)	(0.0100)	(0.0113)
Being physically active	*First stage*	0.440***	0.696***	0.889***	0.805***
		(0.1389)	(0.1814)	(0.1761)	(0.1480)
		10.048	*14.704*	*25.480*	*29.558*
	Second stage	-0.068	0.024	0.019	-0.016
		(0.0896)	(0.0481)	(0.0373)	(0.0430)
Reform definition ...					
... based on education trajectories		X			
... based on year of birth			X	X	X
Assigned years of schooling				X	X
Using current state of residence as proxy					X

Source: NEPS (2018), N=2781; own calculations.

3) N=1783; sample, excluding individuals who never smoked

4) N= 2572; sample excluding individuals who never drink alcohol

Note: Clustered standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Kleibergen Paap Wald F-Statistic in italics; controls OLS: , μ_{state}, $\delta_{state} * cohort$ and ϑ_{cohort} *age, age, age², panel wave, gender; controls IV: μ_{state}, $\delta_{state} * cohort$, and ϑ_{cohort} *age, age, age²; standard errors are clustered for cohorts*state. There is a smaller sample size compared to the estimation presented in Table 3 because of respondents who did move from regions of the former BRD to a federal state of the former GDR; in the IV-regression, some controls are partialled out to adjust for small sample sizes.

7 Conclusion

We complement prior research and revisit the causal effect of education on health for Germany. We theoretically argue that education has an effect on health through higher productive and allocative efficiency, as well as health-related knowledge and skills. The education-health relationship may however be endogenous, because (good) health is a prerequisite for acquiring human capital in the first place, or because other unobservable factors drive positive associations between education and health. A large body of literature addresses this concern and estimates the effect of education on health for example by exploiting exogenous variation in schooling to identify whether the relationship is causal or not. Results from this research, however, provide mixed and, thus, inconclusive evidence (Hamad et al., 2018).

Prior research for Germany is as inconclusive and only little research has been carried out on the causal effect of education on health. We contribute to this literature by addressing limitations of previous studies. We use longitudinal data from the adult cohort of the NEPS and exploit exogenous variation in years of schooling that was induced by a compulsory schooling reform. We add to prior research by employing more precise information on individuals' educational trajectories and on the schooling reform.

We examine educational differences in subjective health status, BMI values, being overweight, being obese, smoking behavior, drinking patterns and physical activity. For individuals' subjective health status, and their obesity propensity, our results are in line with those of Hamad et al. (2018), but contradict those of Kemptner et al. (2011) and Jürges et al. (2011). Our findings also differ from Kemptner et al. (2011) for smoking behavior. They however are in line with the majority of the empirical evidence as presented by Hamad et al. (2018), and Reinhold and Jürges (2010), who report no causal effects of education on smoking behavior. For alcohol consumption, our results are in line with descriptive prior research, which highlights different consumption patterns across different educational groups (e.g. Beard et al., 2016, Bloomfield et al., 2000; Grittner et al., 2012; Cutler and Lleras-Muney, 2010). As Bloomfield et al. (2000) mention, there is clear evidence that those with lower education levels are more likely to drink heavily and abuse alcohol, while more highly educated persons drink more frequently, but less heavily. Results for physical activity are in line with the majority of previous research that suggests no causal effect of education on physical activity (Hamad et al., 2018).

Our results are similar to much of previous empirical research, but most are at odds to those of Kemptner et al. (2011). This highlights the impact of limitations with regard to reform definition and data. We addressed concerns regarding the homogeneity of the effect, the exogeneity of compulsory schooling, and the implementation strategy of the reform. Additional analyses suggest low levels of sensitivity of our estimations, as neither the exclusion of individuals who attended the highest secondary school level, nor individuals who repeated a grade level seem to bias our results. When replicating the implementation strategy of Kemptner et al. (2011), we however see differences in first stage regression results, and some changing patterns in second stage results. Our findings indicate that two-stage least square estimations are highly sensitive to imprecise implementations of the instrumental variable, and proxy measures for identifying treated and non-treated individuals.

The differences of our study and those of Kemptner et al. (2011) might occur for three further reasons. First, we study NEPS respondents who are about 10 years older than those in the German Microcensus data used by Kemptner et al. (2011). We thus estimate even longer lasting effects of education on health for an older sample, which might be empirically different. Additionally, surveys including older respondents tend to be biased by health-related and mortality-caused selectivity, which might weaken the observed link between education and health. Since more highly educated individuals tend to live longer and stay in better health as they grow older, they are more likely present in our sample. Moreover, less educated individuals in these age ranges might be a highly selective group, because it may be only individuals with already good health that take part in the survey (Kratz and Patzina, 2020; Dupre, 2008). For NEPS, selectivity analyses support this assumption (Hammon et al., 2016). Health-related differences between educational groups might therefore be less pronounced when comparing our sample to the one of Kemptner et al. (2011). Second, our small sample size may limit statistical inference of our models. Although test statistics do not indicate a weak instrument, the effect of the reform on schooling years is rather small, and only 6 % of its variance is explained by the reform. Our estimations might thus have low statistical power, and the IV standard errors may be much larger than those of the OLS regressions (Murray, 2006). Third, due to our small sample size, we were not able to take gender differences into account, which might further mask similarities between our results and those of Kemptner et al. (2011).

To conclude, estimating the causal effect of education on health is a challenging task. Although we find no causal effects of education for most of our health outcomes, sensitivity analyses indicate that research should pay more attention to methods and definitions applied when using schooling reforms as exogenous variables. Our results show that approximations and imprecise implementation strategies may explain inconsistencies in previous studies.

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Appendix

Table A1: Results of OLS and IV Results excluding Lower Saxony and Saarland

	OLS	**IV**	
		First-stage	**Second-Stage**
Bad health	-0.010***	0.503***	-0.024
	(0.0030)	(0.1694)	(0.0513)
		8.811	
Body Mass Index	-0.311***	0.503***	0.329
	(0.0522)	(0.1694)	(0.9918)
		8.811	
Being obese	-0.021***	0.503***	-0.064
	(0.0044)	(0.1694)	(0.0935)
		8.811	
Having overweight	-0.031***	0.503***	-0.040
	(0.0056)	(0.1694)	(0.0581)
		8.811	
Smokes currently	-0.021***	0.503***	0.063
	(0.0045)	(0.1694)	(0.0957)
		8.811	
Quitted smoking [1)]	0.020***	0.761***	-0.020
	(0.0055)	(0.2267)	(0.0742)
		11.262	
regular drinking	0.033***	0.503***	0.163*
	(0.0048)	(0.1694)	(0.0836)
		8.811	
Drinking heavily[2)]	-0.002**	0.471***	-0.023
	(0.0008)	(0.1745)	(0.0205)
		7.274	
Being physically active	0.016***	0.503***	-0.132
	(0.0052)	(0.1694)	(0.1052)
		8.811	

Source: NEPS (2018); N=2,439 ;own calculations

1) N=1,578; sample, excluding individuals who did never smoke
2) N= 2,248; sample excluding individuals who never drink alcohol

Note: clustered standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Kleibergen Paap Wald F-Statistic in italic; controls OLS: , μ_{state}, $\delta_{state} * cohort$ and ϑ_{cohort} *age, age, age², panel wave, gender; controls IV: μ_{state}, $\delta_{state} * cohort$, and ϑ_{cohort} *age, age, age²; standard errors are clustered for cohorts*state; in the IV-regression some controls are partialled out to adjust for small sample sizes.