

Different NEETs, different needs?

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Different NEETs, different needs?

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Different NEETs, different needs?

Explaining why vulnerable young people are
more likely to become NEET

DISSERTATION

To obtain the degree of Doctor at Maastricht University,
on the authority of the Rector Magnificus,
Prof. Dr. Pamela Habibović
in accordance with the decision of the Board of Deans,
to be defended in public
on Thursday 13 July 2023, at 13:00 hours

by

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1



INTRODUCTION

In the last decade, the concept of NEET (young people Not in Employment, Education and Training) has been getting increasing scientific attention by researchers. The origin of the concept of NEET was prompted by the increasing concern of policymakers about vulnerable young people who were not well integrated in society. One of the problems at the time was that this group was not registered in the educational statistics and also underrepresented in official youth unemployment statistics, as they were often not entitled to unemployment benefits. The overall feeling was that for this group of young people, the concepts that were used for the adult population like 'unemployed' or 'inactive' were inadequate to describe their situation (Furlong, 2006). This was the underlying reason why this group was defined by something that they were not: not in employment and not in education or training either. The NEET concept includes all young people who are not participating in the labour market and not attending education, and is thus broader than 'unemployed' or 'inactive'. And it has proven to be a useful basis for policy implementation combatting youth inactivity (European Commission, 2010a, 2010b, 2011; OECD, 2010; Eurofound, 2012).

The concept was originally developed in the United Kingdom in the 1990s, but was widely adopted since 2010 by policy makers in the European Union (EU) as an indicator to guide youth-oriented policies on employment, education and training (Eurofound, 2012). According to the European Pillar of Social Rights Action Plan proposed by the European Commission in March 2021 the European NEET rate should be reduced to 9% by 2030 for young people aged between 15 and 29 years (European Commission, 2021).

NEET rates strongly covary with economic trends. Especially in times of economic downturns, NEET risks increase. To illustrate, the number of NEETs has slightly decreased in the last decade. However, because of the recent Covid-19 pandemic and the related economic consequences, the number of NEETs in the EU (aged 15-29 years) increased from approximately 9.1 million in 2019 to 9.8 million in 2020, which is an increase in the NEET rate of 1.1% (from 12.5% to 13.6%). This relates to the fact that (i) young people had more difficulties to stay in education and training, (ii) it became more difficult for school-leavers to find a job, and (iii) young people working especially on temporary contracts or part time were the first ones to lose their job (European Commission, 2021).

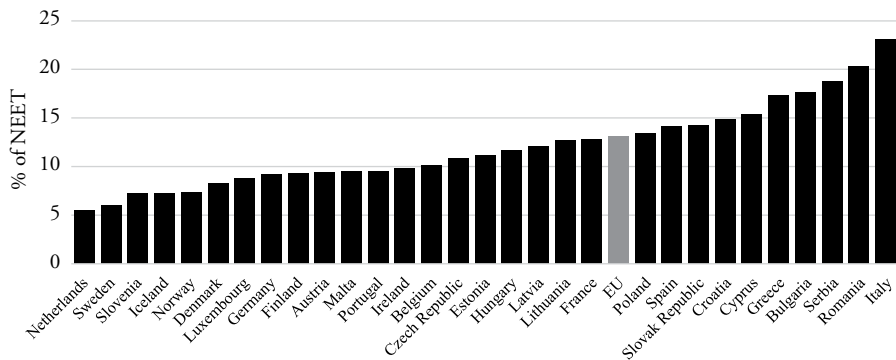
A status as NEET is associated with severe consequences. NEETs are more at risk to experience long-term socioeconomic marginalization and social exclusion, to be involved in criminal activities, to have unintended pregnancies, and to develop severe mental and physical health problems (Bynner & Parsons, 2002; Chen, 2011; Coles et al., 2002; OECD, 2010). Especially when young people become NEET for a more extensive period of time, the consequences can be severe (Eurofound, 2012). Additionally, these consequences do not only impact the NEETs themselves, but also their families and society as a whole (Eurofound, 2012).

Despite the ubiquitous use of the NEETs concept among policy makers, the concept has also been criticized, mostly because of its vagueness. First, the concept has mistakenly been confused with joblessness or labour market discouragement (Elder, 2015). However, the NEET concept is broader as it relates to the share of all young people who are disengaged from the labour market *and* education or training, whether they search for jobs or not. Another critique on the concept is that it lumps together different subgroups (Mascherini, 2019), such as the unemployed, single inactive mothers, long-term sick and disabled, and students taking a gap year. However, NEETs should be considered as a very diverse population having different experiences, needs and characteristics (Furlong, 2006). Additionally, NEETs are often viewed as a sociologically meaningful category, as a social group. However, the patterns in and out of NEET vary across groups and not all NEETs are equally vulnerable. Some young people are voluntarily NEET. This ambiguity about the NEET definition and the urge of policy makers to decrease the NEET rate, increase the risk that policy makers focus on the NEETs that are easiest to reach with the more superficial problems rather than helping the most vulnerable NEETs (Jongbloed & Giret, 2021). Furthermore, the lack of an agreed definition makes it hard for policy makers to identify trends or to make international comparisons (Furlong, 2006). To overcome most of these critiques, the prime focus of current research about NEETs should be on young people who remain NEET for an extensive period of time, while at the same time considering the heterogeneity of the NEETs population, and using a common definition across countries.

The general topic of this dissertation is explaining why certain vulnerable young people are more likely to become NEET. I focus on three important groups of young people. In the first two empirical chapters, I will use international data to focus on two specific groups: young people with low literacy levels and young mothers. In **Chapter 2**, I focus on low-literate young people. Having low literacy levels is the most important predictor of unsuccessful integration in the labour market and society. Low-literate NEETs are therefore more at risk to stay NEET for a long time. Previous literature also shows that NEET is a gendered problem and women are more at risk of becoming NEET than men (Levels, Brzinsky-Fay, Holmes, Jongbloed, & Taki, 2022). In **Chapter 3**, I therefore focus on young mothers who are often not seen as vulnerable because the decision to give birth could be voluntarily. However, in the concept of NEET, a caretaker is also regarded as NEET and there are many indications that this group experiences difficulties in going back to education or work when affordable childcare is not available. For the third group I will focus on early school-leavers using Dutch data (**Chapter 4** and **Chapter 5**). Although early school-leavers are strictly speaking not always NEET, they are very much at risk of becoming NEET at some point in their life (Levels, Brzinsky-Fay, Holmes, Jongbloed, & Taki, 2022). These young people lack the necessary qualifications to find a (stable) job on the labour market and are thus more likely to end up unemployed or to obtain temporary or

precarious work. Therefore, exploring the underlying mechanisms why some young people are more likely to leave school early could also help in decreasing NEET rates.

Besides focusing on these three different groups, the dissertation also takes different perspectives: a macro perspective in **Chapters 2 and 3**, and a meso and micro perspective in **Chapters 4 and 5**. In the first part of this dissertation, the perspective is that individual's risk to become NEET plausibly arises from the interplay between individual and country characteristics. As shown in Figure 1.1, the prevalence of NEETs differs across countries. Part of this could be related to institutional differences, such as the labour market policies, characteristics of the educational systems or the type of welfare regime. One of the points of attention is whether policy interventions reach the groups that are most vulnerable.



Source: Eurostat (2021)

Figure 1.1 - Percentage of young people NEET in 2021 (age 15-29)

As indicated earlier, **Chapter 2** explores to what extent the likelihood of young people being long-term NEET can be explained by low literacy skills. Additionally, I assess how the NEET risk varies across advanced countries, and how this cross-national variation can be explained by education and social policies, in particular the vocational orientation of the education system, the Active Labour Market Policies and the type of welfare state regime. Data from the Programme for the International Assessment of Adult Competencies [PIAAC] including 25 countries has been supplemented with macro-level indicators on these education and social policies. The research questions for this chapter are: *To what extent are low levels of literacy skills associated with a high risk of being long-term NEET? How does this vary cross-nationally? To what extent can cross-national variation be explained by education and social policies?*

Most research on macro-explanations for NEET risks focuses on characteristics of educational systems and labour markets. However, for young mothers, family policies also play an important role in explaining NEET risks. **Chapter 3** explores to what extent the risk that young mothers become NEET is related to the costs of family

policy provisions by disentangling the underlying mechanism between childcare costs and NEET risks. Data from the European Union Labour Force Survey [EU-LFS] including the 2010 ad-hoc module ‘Reconciliation between work and family life’ is used, covering 27 countries. This data is complemented with macro data about the affordability of public childcare. The following three research questions are central: *To what extent do policies that determine the affordability of public childcare (national-level) affect childcare use by young mothers? To what extent does individual-level use of Early Childhood Education and Care (ECEC) reduce young mother’s NEET risks?*

Chapter 4 and **Chapter 5** zoom in on a group that is currently NEET or at risk of becoming NEET: the early school-leavers. Here, the perspective changes to a meso and micro perspective by looking at young people and their families within the Netherlands. The main focus is related to the risk and protective factors in the family that affect early school-leaving. Previous literature shows that parental socio-economic status is strongly associated with children’s risk to early school-leaving (Robinson & Meredith, 2013; Robinson, Long, & Lamb, 2012; Traag & Van der Velden, 2011). However, it remains unclear why this is the case and which underlying mechanisms are important. More insight is needed to guide policies that aim to prevent early school-leaving. Therefore, **Chapter 4** disentangles the different mechanisms underlying the relationship between socio-economic status and early school-leaving in the Netherlands. Data from the Intergenerational Transmission of Skills [ITS] dataset and data from the Netherlands Cohort Study on Education [NCO] are used. Combining the two datasets, I am able to assess the relative contribution of a child’s (non-)cognitive skills, parent’s (non-)cognitive skills, parental educational attainment, and household income to early school-leaving. The main research question is: *What is the relative contribution of different parental resources to children’s risk of early school-leaving?*

Since family dynamics might change over time this could affect the parental resources as well. This makes it not only important to look at the contribution of the different parental resources to early school-leaving, but also to examine what happens when the family dynamics change. Therefore, **Chapter 5** explores how shocks in the family affect early school-leaving in the Netherlands. The term ‘shocks’ indicates disruptive family events that change the family dynamics, such as a parental separation, a large drop in the household income, or parents becoming dependent on social welfare. Usually these shocks do not happen in isolation, but in conjunction. Moreover, they can have antecedents and consequences long before and after the actual shock took place. Additionally, this chapter assesses whether the shocks can be dampened by parent’s level of education. And whether this is related to parent’s initial cognitive skills i.e., information processing skills that are required in education, such as math and language skills, or to other effects of their educational attainment, such as their experience in education that provide the skills and knowledge to navigate successfully in education and help their children with making educational decisions.

The same data as in **Chapter 5** are used to answer the following research questions: *To what extent is the risk of early school-leaving at age 18 in the Netherlands affected by family shocks in the preceding period (age 15-17)? To what extent do skills related to parents' education moderate this relationship?*

The dissertation ends with a brief summary of the findings in **Chapter 6**, followed by a reflection on these findings. Next, policy implications and potential directions for future research are discussed.

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1.1 REFERENCES

- Bynner, J., & Parsons, S. (2002). Social exclusion and the transition from school to work: The case of young people not in education, employment, or training (NEET). *Journal of vocational behavior*, 60(2), 289-309.
- Chen, Y. W. (2011). Once a NEET always a NEET? Experiences of employment and unemployment among youth in a job training programme in Taiwan. *International Journal of Social Welfare*, 20(1), 33-42.
- Coles, B., Hutton, S., Bradshaw, J., Craig, G., Godfrey, C., & Johnson, J. (2002). Literature review of the costs of being “not in education, employment or training” at age 16-18.
- Eurofound. (2012). NEETs - Young people not in employment, education or training: Characteristics, costs and policy responses in Europe. Luxembourg: Publications Office of the European Union.
- European Commission. (2010a). Proposal for a council decision on guidelines for the employment policies of the Member States – Part II of the Europe 2020 Integrated Guidelines. Brussels: European Commission.
- European Commission. (2010b). Youth on the move: an initiative to unleash the potential of young people to achieve smart, sustainable and inclusive growth in the European Union. Luxembourg: Publications Office of the European Union.
- European Commission. (2021). *The European Pillar of Social Rights Action Plan*. Luxembourg: Publications Office of the European Union.
- Eurostat. (2021). Early leavers from education and training by sex and labour status. Retrieved 12 October 2021, from https://ec.europa.eu/eurostat/databrowser/view/edat_lfse_14/default/table?lang=en
- Furlong, A. (2006). Not a very NEET solution. Representing problematic labour market transitions among early school-leavers. *Work, Employment and Society*, 20(3), 553-569.
- Jongbloed, J., and Giret, J.-F. (2021). Quality of life of NEET youth in comparative perspective: subjective well-being during the transition to adulthood. *Journal of Youth Studies*, 125(3), 321-343.
- Levels, M., Brzinsky-Fay, C., Holmes, C., Jongbloed, J., & Taki, H. (2022). *The dynamics of marginalized youth: Not in education, employment, or training around the world*. London: Routledge.
- Mascherini, M. (2019). Origins and future of the concept of NEETs in the European policy agenda. In J. O'Reilly, J. Leschke, R. Ortlieb, M. Seeleib-Kaiser, & P. Villa, (Eds.), *Youth labor in transition* (pp. 503-529). Oxford: Oxford University Press.
- OECD. (2010). *Off to a good start? Jobs for youth*. Paris: OECD Publishing.
- Robinson, E., & Meredith, V. (2013). Family factors in early school leaving. *Journal Of The Home Economics Institute Of Australia*, 20(2), 30-40.
- Robinson, L., Long, M., & Lamb, S. (2012). *How young people are faring*. Melbourne: The Foundation for Young Australians.

- Traag, T., & Van der Velden, R. (2011). Early school-leaving in the Netherlands: The role of family resources, school composition and background characteristics in early school-leaving in lower secondary education. *Irish Educational Studies*, 30(1), 45-62.
- Van Vugt, L., & Levels, M. (2022). Can labour market policies help to reduce long-term NEETs? In M. Levels, C. Brzinsky-Fay, C. Holmes, J. Jongbloed, & H. Taki (Eds.), *The dynamics of marginalized youth* (pp. 219-232). London: Routledge.
- Van Vugt, L., Levels, M., & Jongbloed, J. (2022). How long-term NEET are explained by family policies in OECD countries. In M. Levels, C. Brzinsky-Fay, C. Holmes, J. Jongbloed, & H. Taki (Eds.), *The dynamics of marginalized youth* (pp. 233-247). London: Routledge.
- Van Vugt, L., Van der Velden, R., Levels, M., & Brzinsky-Fay, C. (2022). The role of education systems in preventing NEETs. In M. Levels, C. Brzinsky-Fay, C. Holmes, J. Jongbloed, & H. Taki (Eds.), *The dynamics of marginalized youth* (pp. 205-218). London: Routledge.

2

THE LOW SKILLS TRAP

The Failure of Education and Social Policies in Preventing Low-Literate Young People from being Long-Term NEET

This chapter is joint work with Mark Levels and Rolf van der Velden. This chapter is published in the *Journal of Youth Studies* (2022). We thank the participants of the ECSR 2020 Online Conference, the 2018 ISA RC28 Spring Meeting in Seoul, Republic of Korea and the ORA-project meeting NEETs 2018 in Kyoto, Japan for their valuable comments and suggestions. I would also like to thank Arie Glebbeek, Melline Somers and Katarina Weßling for their valuable comments and suggestions on an earlier draft of this paper.

2.1 ABSTRACT

This chapter investigates to what extent the likelihood of young people being long-term NEET can be explained by low literacy skills, how this varies across advanced countries, and how this cross-national variation can be explained by education and social policies. We use PIAAC data and include macro-level indicators on education and social policies. We analyse the likelihood of being long-term NEET versus being in employment or in education/training among some 34,000 young people aged 20-30 from 25 countries. We find that low-literate young people are more likely to be long-term NEET. While NEET risks are associated with countries' institutional characteristics, this does not mean that these characteristics and policies always work in favour of low-literate young people. Although high levels of (enabling) ALMP generally reduce the risk of being NEET, they do so less for low-literate young people. Additionally, young people living in social-democratic welfare states are less likely to be NEET, but low-literate young people seem to profit less from this.

2.2 INTRODUCTION

In 2019, 13% of young people aged 15-29 in OECD countries were Not in Employment, Education or Training (“NEETs”) (OECD, 2020a). This risk of being NEET is likely to be associated with a lack of basic skills, such as literacy skills. Literacy is a fundamental, “key information-processing skill” (OECD, 2013a), and while such skills are crucial to learn and obtain new knowledge, not everybody acquires them to a sufficient degree. People with low literacy skills are generally less integrated in society. They are more likely to drop out of school and to be unemployed, and they are also less politically and socially involved (Finnie & Meng, 2001; Leuven, Oosterbeek & Van Ophem, 2004; Rudd, Kirsch & Yamamoto, 2004; Hernandez, 2011; OECD, 2013a, 2015). Phrased differently, low-literate young people lack the skills that are important for success in school and on the labour market, and are therefore disproportionately more likely to become NEET (OECD, 2015). This chapter studies the extent to which young people with low literacy skills are more likely to be long-term NEET compared to young people with higher literacy skills, and to what extent relevant institutions and policies serve as a safety-net for these low-literate people.

The concept of NEET originates in the wish of policymakers to identify young people who are not well integrated in society, mainly because they ‘disappear from the radar’: They are not registered in education, but often also not officially registered as ‘unemployed’ because they are not entitled to unemployment benefits yet (Eurofound, 2017).¹ NEETs are regularly framed as a societal problem (Eurofound, 2012), and policymakers try to decrease the number of NEETs and design policies to stimulate the integration of these young people into the education/training system or the labour market (Eurofound, 2012; 2017). These institutional arrangements and social policies contribute to both education and labour market participation, and some institutions specifically support young people in their school-to-work transition (Breen, 2005; Gebel & Giesecke, 2011; Levels, Van der Velden & Di Stasio, 2014). However, most of these institutional arrangements and social policies are general in nature and not specifically targeted towards the most vulnerable group of low-literate young people. It is not clear to what extent the educational and social safety-nets work equally well for the lower and the higher literate young people.

Therefore, we explore to what extent some institutional characteristics not only reduce the NEET risk in general, but also specifically prevent vulnerable low-literate young people to become NEET. Our research questions are: *To what extent are low levels of literacy skills associated with a high risk of being long-term NEET? How does*

¹ There is some critique on the concept of NEET as well, mainly because it lumps together different subgroups of people who are inactive, but who are not equally vulnerable. This causes heterogeneity in the NEET category. One way of getting closer to using the NEET concept to measure vulnerability is by focusing on those who remain NEET for a longer time period (see for example: Levels et al., 2022).

this vary cross-nationally? To what extent can cross-national variation be explained by education and social policies?

To answer these research questions, we use data from the Programme for the International Assessment of Adult Competencies [PIAAC] (OECD, 2013b). PIAAC is a large cross-national adult literacy survey of adults in 33 advanced countries. The data contain information on many of the individual-level variables commonly used to explain NEET risks, such as educational attainment, work experience, socioeconomic background, migration background, family situation, health, etc. (Coles et al., 2002; Strelitz & Darton, 2003; Cassen & Kingdon, 2007; Social Exclusion Task Force, 2008; Eurofound, 2012). We link these data to a country database with characteristics on education and social policies, allowing us to investigate how individuals with low literacy skills fare in different institutional settings.

Our analyses contribute to the literature in two main ways. First, we contribute to the literature on low literacy. When looking at school and labour market success, the literature mainly focuses on the level of education as a proxy for human capital, rather than on an individual's actual skills level (OECD, 2018). However, while education is likely to enhance literacy skills and is indeed strongly correlated with it, skills and educational attainment cannot and should not be equated. There is considerable skills heterogeneity within educational attainment groups and the skills distribution of educational attainment groups overlap considerably, with the most strongly literate lower educated individual being more literate than a considerable group of middle educated individuals. These underlying skill differences are likely drivers of relevant outcomes (Levels, Van der Velden & Allen, 2014; OECD, 2015).

Second, we advance the literature on institutions and NEETs. Individual's risk to become NEET plausibly arise from interactions between individual (life-course) characteristics and countries' education and social policies (Hodkinson, 1996; Hodkinson & Sparkes, 1997; Kogan & Müller, 2003; Müller, 2005). As such, the effectiveness of institutions and policies to combat NEET varies between different social groups. Completely disillusioned and disengaged young people with low literacy skills are likely to respond very differently to institutional incentives than, for instance, high-literate young people who might also have difficulties making the school-to-work transition. These interactions are rarely studied and ill-understood. For example, we found that much of the literature that takes the relevance of institutions for young peoples' participation in education and the labour market into account, focus on young people in general and not specifically on NEETs (Van der Velden & Wolbers, 2003; Breen, 2005; Bol & Van de Werfhorst, 2011; Gebel & Giesecke, 2016).

2.3 THEORY

To provide a theoretical explanation for the relationship between having lower literacy skills and being long-term NEET, we start by identifying various mechanisms through which individual and institutional characteristics generate NEET periods during a young individual's life course. Our theoretical frame explains why some young people do not have a job and are not in education or training either.

Literacy skills are part of young people's human capital and are important predictors of economic and social participation. These skills are important for productivity, i.e. for success on the labour market, but also necessary to develop other skills, i.e. to be successful in education. One of the key factors that explain why some young people become NEET may be differences in the extent to which they have mastered relevant skills (OECD, 2015; Gladwell, Popli & Tsuchiya, 2016). Young people with low general skills are at greater risk of dropping out of school (Cairns, Cairns & Neckerman, 1989; Audas & Willms, 2001; Traag & Van der Velden, 2011). This could be because young people with low skills have more difficulty in acquiring and developing further skills. In addition, low-skilled youth are also less likely to engage in training or invest in further schooling, for example because their experience has taught them that the low returns to education do not justify an additional investment (Mincer, 1974), or because they do not expect to be able to complete the (additional) education programme (cf. Fan & Wolters, 2014).

This makes them more likely to leave education and try to find a job on the labour market. However, they may be hampered in that effort, as having lower literacy skills also decreases the chances of success on the labour market (Barrett, 2012). According to various matching theories (Kalleberg & Sorensen, 1979; Logan, 1996; Müller, 2005) and the queuing theory (Thurow, 1975; Sørensen & Kalleberg, 1981), employers strive for the best possible match, given their preferences, opportunities and constraints. Employers rank all available applicants in an imaginary queue on the basis of expected training costs: the applicant who is the first in line, will be hired (Thurow, 1975). Consequently, young people with low skills are more likely to end up at the back of the job queue and are therefore less likely to find and keep a job. For this reason, we expect that:

*Low-literate young people are generally more likely to be
long-term NEET (Hypothesis 1).*

In theory, some institutional characteristics should “protect” low-skilled people and thus weaken the relationship between low skills and being NEET, while other institutional characteristics might do the opposite and strengthen this individual-level relationship. In the next paragraphs, we will argue that the vocational orientation of an educational system may affect the extent to which low-literate young people

are likely to be long-term NEET. Furthermore, we will examine the extent to which activating labour market policies (ALMP) and welfare state regimes may affect the relationship between low literacy and the likelihood of being long-term NEET.

2.3.1 Vocational orientation

In countries that mainly offer vocationally oriented education, young people with low literacy skills have the opportunity to continue studying in vocational tracks in upper secondary education. This may offer an alternative for low-literate young people and give them a protected position on the labour market (Shavit & Müller, 2000; Ryan, 2001). Moreover, in vocationally oriented educational systems, vocational tracks have more prestige than in more academically oriented systems (Shavit & Müller, 2000; Solga, 2002; Iannelli & Raffe, 2007).

Previous literature strongly suggests that vocational education systems indeed smoothen the transition from school to work (Van der Velden & Wolbers, 2003; Breen, 2005). From the employers' perspective, we expect that in vocationally oriented systems the level of general skills – including literacy skills – is less important, because employers want to hire people who need less training and are directly productive on the job. Therefore, they will place less emphasis on general skills and more emphasis on occupation-specific skills. In these labour markets, young people with a vocational degree have fairly good labour market opportunities, since their skills are directly applicable in the workplace.

On the other hand, in countries where the education system is less vocationally oriented, general skills become more important in the hiring process and tertiary education is more often required on the labour market (Shavit & Müller, 2000). Here, higher literacy skills indicate higher levels of trainability. In addition, in these countries vocational education is more stigmatized and regarded as a safety net that serves as a remedial option for young people who are not able to study at higher educational levels (Shavit & Müller, 2000; Solga, 2002; Iannelli & Raffe, 2007).

Based on these arguments, we expect that for vocationally educated the effect of having low literacy skills on the chance to become NEET is lower in countries that have a strong vocational orientation compared to countries that mainly offer academic education. This leads to the following hypothesis:

Vocationally educated young people with low literacy skills are generally more likely to be long-term NEET than vocationally educated young people with higher literacy skills; however, this individual-level relationship is less strong in countries where the education system is more vocationally oriented (Hypothesis 2).

2.3.2 Activating labour market policies (ALMP)

Active labour market policies are aimed to improve the educational and labour market prospects of young people. We expect that the higher the amount of public spending on ALMPs in a country, the more likely it is that the country is improving the educational and labour market prospects of young people – for instance, by training or re-training young people in skills that are required on the labour market. Therefore, we expect the effect of having low literacy skills on the chance to become NEET to be lower in countries with higher levels of public spending on ALMPs compared to countries with lower levels of such public spending:

Low-literate young people are generally more likely to be long-term NEET, but this individual-level relationship is less strong in countries with higher levels of public spending on ALMPs (Hypothesis 3).

ALMPs can be characterized as “enabling” and “enforcing” policies (Dingeldey, 2007; Knotz, 2012). Enabling policies assume that certain jobseekers lack the necessary skills to enter or re-enter the labour market. These policies facilitate training, for example, but also make it easier to combine work and family care. We expect that in countries that mainly focus on enabling policies, low-literate young people are less likely to be long-term NEET because these policies focus on training or re-training young people in skills that are demanded by the labour market. In addition, these policies enable young people to find a job that fits their skills. Therefore, we expect the effect of having low literacy skills on the chance to become NEET is lower in countries with strong enabling ALMPs compared to countries with weaker enabling ALMPs. We assume that:

Low-literate young people are generally more likely to be long-term NEET, but this individual-level relationship is less strong in countries with stronger enabling ALMPs (Hypothesis 4).

In contrast, enforcing policies assume that some people lack the motivation or incentives to find a job. These policies aim to tighten the readiness-to-work requirements and suitability criteria by, for instance, reducing the level and duration of financial benefits (Knotz, 2012). Rather than stimulating young people in training, re-training or further education, these policies force young people into a job or education, independently of their level of skills. Therefore, we expect the effect of having low literacy skills on the chance to become NEET to be lower in countries with strong enforcing ALMPs, compared to countries with weaker enforcing ALMPs. Hence, we hypothesize:

Low-literate young people are generally more likely to be long-term NEET, but this individual-level relationship is less strong in countries with stronger enforcing ALMPs (Hypothesis 5).

2.3.3 Welfare state regimes

One of the aims of welfare state regimes is to help vulnerable people by offering social security. However, the way welfare states are organized varies and we expect that this will also create differences among the risks for low-literate young people to become NEET. Welfare state regime types are indeed associated with NEET rates and patterns (Jongbloed & Giret, 2021; Pastore 2018). The most widely used classification of welfare states is the one developed by Esping-Andersen (1990). He distinguishes social democratic, liberal and the conservative welfare states. This classification has limitations as it seems to fit less well for the Mediterranean, and transitional (post-socialist) countries (Arts & Gelissen, 2002). Various changes to and expansions on Esping-Anderson's classical categorisation have been proposed (for example: Gallie and Paugam, 2000; Rhodes and Ferrera 2000), and the conceptualisation policy and categorisation of countries into ideal-typical regimes has strongly influenced the literature on transition regimes (Walther, 2006; Pohl and Walther, 2007; Hadjivassiliou, Eichhorst, Tassinari & Wozny, 2016). Building on this literature, in addition to the three clusters of welfare states distinguished by Esping-Anderson, we distinguish a Mediterranean cluster (Southern-European countries) and a transitional cluster (East-European countries) (Hadjivassiliou et al., 2016).

The social-democratic welfare states are characterized by high levels of decommodification and strong universalism. It stimulates work-engagement and individual independency; however, it also includes highly distributive benefits not dependent on individual contributions (Esping-Andersen, 1990). One would expect therefore that groups at risk, such as people with low literacy levels, might receive additional support in such welfare states to help them participate fully in society. In liberal welfare states there is low decommodification and strong individualistic self-reliance. Here, the rights to social benefits are limited to the bare minimum which is meant to stimulate work rather than using benefits (Esping-Andersen, 1990). At the same time, solidarity is low, and this implies that participation in society is seen as an individual responsibility with few supports for groups at risk. The conservative welfare states follow a moderate level of decommodification and benefits are based on former contributions and status (Esping-Andersen, 1990). They are more corporatist in nature and the role of state is seen as complementary to the role of families. The Mediterranean welfare states are more strongly family-oriented, with little state intervention, a more fragmented social safety net and more particularism and clientelism (Ferrera, 1996). The transitional welfare states are the former communist countries with the previously associated strong state intervention and solidarity, which have undergone a dramatic

change towards a liberal market-driven economy, but are lacking the basic social safety nets that characterise liberal countries (Kogan & Müller, 2003).

Based on this typology of welfare states we expect that the effect of literacy on young people's chance to become NEET is lower in social-democratic welfare states (because these welfare regimes are more likely to help the most vulnerable people) and higher in Mediterranean and transitional welfare states (due to the lack of state interventions and the relatively under-developed ALMPs; Hadjivassiliou et al., 2016). Therefore, we hypothesize:

Low-literate young people are generally more likely to be long-term NEET, but this relationship is less strong in social-democratic welfare states than in Mediterranean and transitional welfare states (Hypothesis 6).

2.4 DATA, MEASUREMENTS & METHODS

2.4.1 Data

We use data from the Programme for the International Assessment of Adult Competencies (PIAAC), collected in 24 participating countries between August 2011 and March 2012 and in 9 additional countries between April 2014 and March 2015. The survey is designed to provide valid and reliable estimates of adults' competences in key information-processing skills, to identify proficiency differences between sub-groups of the population, to understand development, maintenance and use of skills, as well as to determine the impact of proficiency levels on life chances. Country samples contain some 5,000 adults between the ages of 16 and 65. Respondents were interviewed in computer-assisted personal interviews and took a computer-based test (although pencil-and-paper data collection strategies were also used). Respondents were given assessment tests designed to directly measure their general skills. More specifically, these tests measure numeracy and literacy skills, and respondents' capacity to solve problems in technology-rich environments. The survey is cross-culturally and cross-nationally valid.

To prepare the data for analyses, we selected people between the ages of 20 and 30.² Data from Russia were not analysed for technical-administrative reasons; data from Cyprus, Lithuania, Singapore and Turkey were not analysed because data were missing for some or all of the macro-indicators; Chile was not analysed because of the particularly high proportion of low-literate young people. We also deleted the specific oversample of PISA 2000 survey respondents in Denmark because these targeted

² We limited the sample to young people aged 20-30, because in most countries compulsory education ends after age 18 (OECD, 2018).

respondents were not part of the international target population definition (OECD, 2013a). Finally, we weighted data from Canada, since the original Canadian sample was much larger than the samples in other countries. To weight back, we drew a random sample of 35%. These selections resulted in a total sample of $N=34,347$. Lastly, we deleted cases with missing values on the NEET variable ($N=403$) and the other individual-level variables ($N=221$). These selections resulted in a total working sample of $N=33,742$ respondents aged 20-30 from 25 countries.

2.4.2 Measurements

Descriptive statistics of all variables are presented in Table 2.1. Below is a description of how the variables were measured.

Dependent variable

- *Employed, education/training or long-term NEET*: We construct a variable indicating whether young people have been long-term NEET using three separate questions whether the respondent (a) has had paid work, (b) participated in formal education or (c) participated in non-formal education³. Respondents who did not participate in any of these activities in the period of 12 months preceding the survey are labelled as long-term NEET. The reason to take a period of 12 months or more is to exclude respondents whose NEET status is largely transitory, such as short-term unemployed, and absence of work due to illness or pregnancy. The time spent as NEET is a useful way to distinguish between NEETs who are vulnerable and those who are not (see for example: Levels et al., 2022) Respondents who participated in paid work were labelled as employed, and respondents who participated in formal or non-formal education were labelled as in education/training. If young people were both employed and in education/training, we labelled them as being employed.

Country-level variables

- *Vocational orientation*: Bol and Van de Werfhorst (2014, 2016) combined two data sources (from the OECD and UNESCO) measuring the percentage of students enrolled in upper secondary vocational programmes. The variable was standardized by the original authors. The index we use to measure vocational orientation has a mean of 0.28, a standard deviation of 0.91 and a range from

3 The concept of NEET explicitly excludes people that are in education or in training. In the PIAAC data, non-formal education is defined as “any organised and sustained educational activities” outside the definition of formal education that “may [. . .] take place both within and outside educational institutions, and cater to persons of all ages” (OECD, 2011, p. 31). For example, courses through open and distance education, organised sessions for on-the-job training or training by supervisors or co-workers, seminars or workshops.

-1.84 to 1.74; the higher the score, the more strongly vocationally oriented the system is.

- *ALMP*: We use public expenditure on active labour market policies as a percentage of GDP provided by the OECD (OECD, 2020b). We use data from the year before the year of the interview and standardized this variable (mean 0, standard deviation 1, range from -1.17 to 3.57). The higher the score, the higher the expenditure on ALMPs.
- *Enablement*: This indicator is based on the indicator constructed by Knotz (2012). The indicator is based on several underlying dimensions of enablement, such as wage subsidies, job counselling, training, family services, etc. (see Knotz, 2012). We standardize this variable (mean 0, standard deviation 1, range from -1.60 to 1.96). The higher the score, the greater the effort in enabling ALMPs.
- *Enforcement*: We use the enforcement indicator from Knotz (2012). The scores are computed as averages of the effort scores on the underlying dimensions of enforcement such as low benefit level, obligation to job-search, etc. (see Knotz, 2012). We standardize this variable (mean 0, standard deviation 1, range from -1.95 to 1.99). The higher the score, the greater the effort in enforcement ALMPs.
- *Welfare states*: We cluster countries into the three types of welfare states as indicated by Esping-Andersen (1990), and add two additional clusters, Mediterranean and transitional welfare states, based on Hadjivassiliou et al. (2016). Based on Gal (2010), we include Israel in the Mediterranean welfare states. South-Korea is left out of the analyses (For an overview of the countries per cluster, see Appendix A, Table A2).
- *Output gap*: To control for the business cycle we include the output gap (i.e., the difference between the actual and potential GDP expressed as a percentage of GDP) of the year before the interview (OECD, 2019a). We standardize this variable (mean 0, standard deviation 1, range from -3.96 to 1.26). A positive value indicates a higher demand for workers. This indicator is commonly viewed as a better indicator for demand-supply imbalances than unemployment statistics. However, we do run a robustness analysis using unemployment statistics as well (see Appendix A, Table A6).⁴

Individual-level variables

- *Low literacy skills*: PIAAC measures three types of general skills: literacy skills, numeracy skills, and skills related to problem solving in technology-rich environments (OECD, 2013a, 2016). These skills measures are

⁴ It should be noted that labor market conditions vary within countries, between regions. As our aim is to look at the association between national institutional characteristics and individual-level outcomes, we control for labor market conditions at the national level.

constructed using adaptive testing methods. We focus on the domain of literacy skills.⁵ Literacy is defined as “understanding, evaluating, using and engaging with written texts to participate in society, to achieve one’s goals, and to develop one’s knowledge and potential” (OECD, 2012b). It does not include the ability to write or produce text. After the test, ten plausible values are generated that represent the respondent’s literacy skills.

In line with the literacy skills levels constructed by the OECD (2016), we define young people as low-literate when they score at or below level 1 (score below 226) on the literacy test. This is the lowest level of literacy. People who score at level one can “complete simple forms, understand basic vocabulary, determine the meaning of sentences, and read continuous texts with a degree of fluency” (OECD, 2013a, p.67) and we compare them with young people with a score above level 1 (score 226 or above). To measure this, we estimate for each individual the level of literacy skills (at or below vs. above level 1) based on the ten plausible values provided by PIAAC. We account for both the sampling error component and the variance due to imputation of the literacy scores (for detailed information about PIAAC and technical issues, see: OECD, 2016). Figure 2.1 shows the percentage of young people with low literacy skills per country, based on the ten plausible values.⁶ Japan (2.1%), Korea (3.9%) and Finland (4.3%) have the lowest percentages of young people with low literacy skills, while Israel (20.7%), Italy (22.1%) and Greece (25.7%) have the highest.

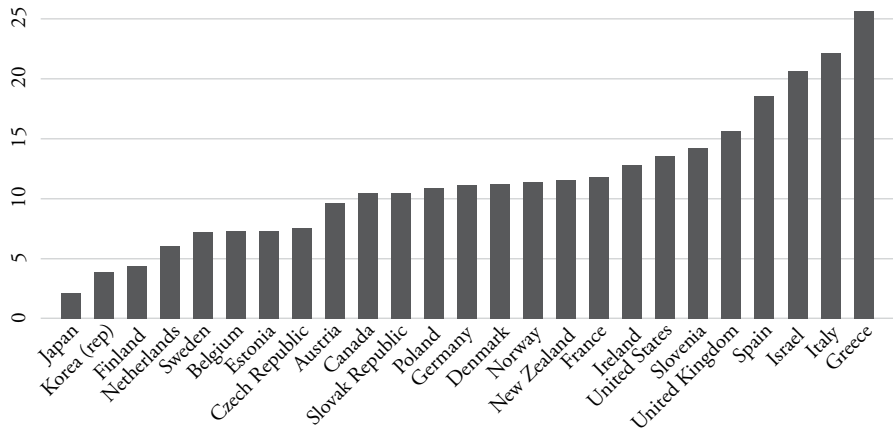


Figure 2.1 - Percentage of low-skilled young people across countries

5 Literacy and numeracy are very strongly correlated ($r = .9$), and problem-solving skills were only measured for two-thirds of the sample.
6 All percentages are estimated via the REPEST command by Arvisati & Keslair (2014).

Table 2.1 - Descriptive statistics

	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>Min.</i>	<i>Max.</i>
<i>Dependent variables</i>					
NEET	33,742	0.08		0.00	1.00
Employed	33,742	0.76		0.00	1.00
Education/training	33,742	0.15		0.00	1.00
<i>Country-level variables</i>					
Vocational orientation	24	0.28	0.91	-1.84	1.74
ALMP	24	0.00	1.00	-1.17	3.57
Enablement	17	0.00	1.00	-1.60	1.96
Enforcement	17	0.00	1.00	-1.95	1.99
<i>Welfare states</i>					
Social-democratic	24	0.18		0.00	1.00
Conservative	24	0.13		0.00	1.00
Liberal	24	0.22		0.00	1.00
Transitional	24	0.33		0.00	1.00
Mediterranean	24	0.13		0.00	1.00
<i>Control variables</i>					
Male	33,742	0.48		0.00	1.00
Age	33,742	24.77	3.16	20.00	30.00
<i>Migration status</i>					
Native	33,742	0.88		0.00	1.00
First generation migrant	33,742	0.09		0.00	1.00
Second generation migrant	33,742	0.03		0.00	1.00
<i>Parental education level</i>					
Both parents low educated	33,742	0.14		0.00	1.00
At least one medium educated parent	33,742	0.46		0.00	1.00
At least one higher educated parent	33,742	0.35		0.00	1.00
Missing	33,742	0.05		0.00	1.00
<i>Educational attainment</i>					
Low educated	33,742	0.13		0.00	1.00
Medium educated	33,742	0.56		0.00	1.00
High educated	33,742	0.32		0.00	1.00
Vocational track	33,742	0.36		0.00	1.00
Output gap	24	0.00	1.00	-3.96	1.26

Notes: the descriptive statistics for the sub-sample of vocationally educated young people (iscsd 3/4) can be found in Appendix A, Table A1; for an overview of the values on country-level variables per country see Appendix A, Table A2.

- *Male*: A dummy signifying whether the respondent is male or female.
- *Age*: Included as a continuous variable. Additionally, we include a squared term for age to account for non-linearity of the relation between age and being long-term NEET.
- *Migration status*: Measured using dummies to distinguish non-immigrants, first-generation immigrants (both parents and respondent foreign born) and second-generation immigrants (both parents foreign born, respondent born in test country). Non-immigrants are the reference category.
- *Parental education level*: A categorical variable indicating the educational attainment of the most highly educated parent. We distinguish between two lower-educated parents, at least one medium-educated parent and at least one higher-educated parent. We also include a dummy for missing values. Respondents with two lower-educated parents are the reference category.
- *Educational attainment*: Is based on a collapsed version of the International Standard Classification of Education (ISCED) 2011. We distinguish three levels: low education (ISCED 0/1/2/3C short), medium education (ISCED 3A/3B/3C long/4A/4B/4C) and high education (ISCED 5A/5B/6). A low education level forms the reference category.
- *Vocational track*: A dummy signifying an academic or vocational track.

2.4.3 Methods

Our hypotheses focus on explaining the individual-level relation between having low literacy skills and being long-term NEET. We assess whether this relation differs cross-nationally and is moderated by institutional characteristics. To test our hypotheses, we perform multinomial regression analyses to account for the different possible outcomes: in employment, in education or training or long-term NEET. We add cluster standard errors to correct for the hierarchical clustering of respondents within countries. In addition, we apply the Final Weight “spfwto” to the model to make the data representative of the target population. We estimate these models using the *mlogit* package in Stata 15.

Since PIAAC is a cross-sectional data source, results should be interpreted as associations rather than causal effects. Therefore, our analyses do not account for reverse causality between literacy skills and the risks of being long-term NEET. Also, we cannot control for unobserved heterogeneity (e.g. factors such as motivation and abilities) that may obscure the relationships. These caveats should be taken into consideration when evaluating our results. Thus, our results should not be interpreted as an attempt to formally identify the causal impact of education or social policies. However, we may evaluate whether or not our coefficients are in line with what we would expect to see if we would assume a causal relationship.

2.5 RESULTS

2.5.1 Descriptive analyses

Figure 2.2 presents percentages of the 20-30-year-old population that are long-term NEET in the various countries. A large cross-national variation can be observed. The countries with the lowest proportions of long-term NEETs are the Netherlands (2.1%), Norway (2.9%) and Austria (3.2%). Countries with high proportions of long-term NEETs include Italy (15.6%), the Slovak Republic (16.7%) and Greece (19.0%). The proportion of long-term NEETs in the PIAAC data is generally lower than what is reported in the literature (Eurofound, 2012). However, the pattern in the observed rates across countries closely resembles what we know from the literature (Eurofound, 2012).

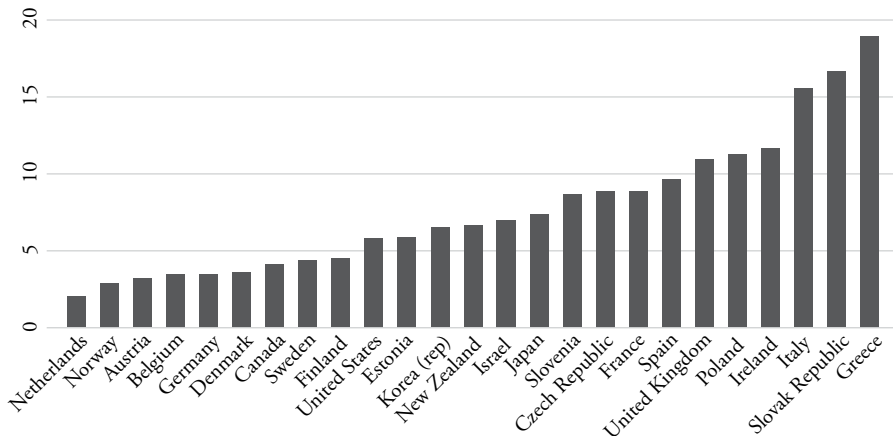


Figure 2.2 - Percentage of long-term NEETs per country

Figure 2.3 (Appendix A, Table A3) shows the relationship between low literacy skills and being long-term NEET. While the strength of the relationship varies across countries, it shows that in all countries the relation is positive and for most countries it is also significant. This indicates that having low literacy skills generally increases the risk of being long-term NEET, which is in line with Hypothesis 1. However, the figure also indicates that there are considerable cross-national differences in the strength of the relation, and that in some countries (e.g. Japan, Italy, the United States, Korea, and Finland) the relation is not statistically significant.

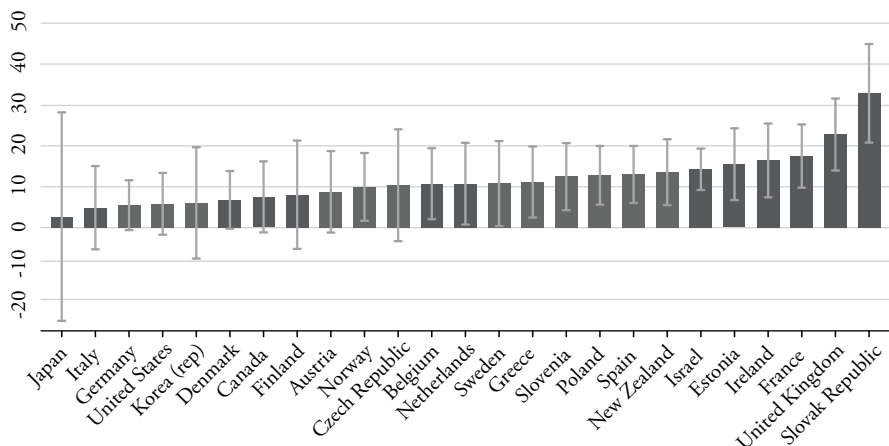


Figure 2.3 - Association between low literacy skills and being long-term NEET

2.5.2 Multinomial regression analyses

We perform a multinomial regression analysis to account for young people’s likelihood of being in employment or in education/training rather than being long-term NEET. For the margin plots see Appendix A, Figure A1.

In Table 2.2, Model 1, we expected that the relationship between vocationally educated young people with low literacy skills and being long-term NEET, would be less strong in countries where the education system is more vocationally oriented. However, the interaction term in Model 1b is not statistically significant, so we refute Hypothesis 2.

Model 2 shows the results of ALMPs in general. We find that in countries with high levels of ALMPs, young people are less likely to be long-term NEET, mainly because they are in education or training. However, the cross-level interaction shows that low-literate young people do not profit from this: In countries with high levels of ALMPs, low-literate young people are more likely to become NEET and less likely to be either employed or in education/training. This is the opposite of what we expected in Hypothesis 3.

Model 3 shows similar results for enabling ALMPs. We find evidence that young people in countries with high levels of enabling ALMPs are in general more likely to be in education/training than to be long-term NEET (Model 3a), but this does not hold for young people with low-literacy skills. The interaction term in Model 3b shows that low-literate young people profit less from enabling ALMPs than high-literate young people. This is the opposite of what we expected and refutes Hypothesis 4.

When we look at enforcing ALMPs, we observe in Model 4a that the main effect of enforcing ALMPs is negative: The higher the level of enforcing ALMP in a country, the less likely young people are to be in education/training and the more likely they are to be NEET. However, this holds stronger for high-literate than for low-literate

young people. Low-literate young people are in fact more likely to be in education/training than to become NEET. This partially confirms Hypothesis 5.

Lastly, Model 5 shows the results on the differences between types of welfare states. We find that young people living in social-democratic welfare states are more likely to be employed or in education/training than in any of the other types of welfare states. However, if we look at the interaction terms, none of the coefficients are significant in the education/training versus NEET specification. This indicates that in the different welfare states (conservative, liberal, transitional, and Mediterranean), having low literacy is not related to the likelihood to be NEET instead of being in education/training. The same holds for the social-democratic welfare states, as the main effect of having low literacy skills is also not significant. In the specification of being employed versus being NEET, we find the opposite of what we expected. The main effect for having low literacy skills in Model 5b (i.e., the association for low-literate young people in social-democratic welfare states) is significant, indicating that low-literate young people in these welfare states are less likely to be employed than to be NEET. On the other hand, many of the interaction terms for the other types of welfare states are borderline positive significant, indicating that in these other welfare states, low-literate young people are relatively less affected by the overall higher likelihood in these countries to become NEET instead being employed. We therefore refute Hypothesis 6.

Table 2.2 - Multinomial regression estimates on the relationship between low literacy skills and long-term NEET, employment versus education/training

Employed	M1a	M1b	M2a	M2b	M3a	M3b	M4a	M4b	M5a	M5b
Low literacy skills (Higher literacy skills=Ref.)	0.639 (0.196)	0.641 (0.200)	0.684* (0.118)	0.623*** (0.086)	0.717~ (0.137)	0.590** (0.113)	0.709~ (0.134)	0.664* (0.132)	0.696* (0.107)	0.332*** (0.093)
Vocational orientation	0.922 (0.215)	0.925 (0.212)								
Low literacy*Vocational orientation		0.979 (0.263)								
ALMP			1.164 (0.131)	1.237~ (0.136)						
Low literacy*ALMP			0.788* (0.081)							
Enablement					1.076 (0.119)	1.155 (0.124)				
Low literacy*Enablement					0.739* (0.084)					
Enforcement							1.093 (0.088)	1.049 (0.092)		
Low literacy*Enforcement								1.136 (0.130)		
Welfare states (Social-Democratic = Ref.)										
Conservative									0.371*** (0.109)	0.313*** (0.104)
Liberal									0.461** (0.125)	0.395*** (0.109)
Transitional									0.161*** (0.036)	0.144*** (0.037)
Mediterranean									0.300***	0.240***

Low literacy*Conservative												(0.089)	(0.090)
Low literacy*Liberal													2.308-
Low literacy*Transitional													(1.108)
Low literacy*Mediterranean													2.019-
													(0.761)
													1.631
													(0.540)
													2.692*
													(1.132)
Education/training	M1a	M1b	M2a	M2b	M3a	M3b	M4a	M4b	M5a	M5b			
Low literacy skills (Higher literacy skills=Ref.)	0.418* (0.145)	0.423* (0.150)	0.702 (0.216)	0.576*** (0.094)	0.776 (0.261)	0.533* (0.135)	0.797 (0.266)	0.570* (0.142)	0.708 (0.217)	0.579 (0.223)			
Vocational orientation	1.217 (0.291)	1.219 (0.296)											
Low literacy*Vocational orientation		0.969 (0.308)											
ALMP			1.517*** (0.191)	1.654*** (0.210)									
Low literacy*ALMP				0.595* (0.147)									
Enablement					1.576* (0.281)	1.734** (0.310)							
Low literacy*Enablement						0.564* (0.137)							
Enforcement							0.660** (0.091)	0.598*** (0.079)					
Low literacy*Enforcement								1.722** (0.306)					

2.5.3 Additional analyses

We have conducted several additional analyses to check whether our results are robust. First, we keep the number of countries equal across all analyses by leaving out the countries with at least one macro-indicator missing (see Appendix A, Table A5), and find that our conclusions did not substantially change.

Second, to include a different measure of labour market shortages, we controlled for youth unemployment rate rather than output gap (see Appendix A, Table A6). We found that this did not change our conclusions.

Third, we checked to what extent the results change when we define young people as low-literate when they score at or below level 2 (score below 276) (see Appendix A, Table A7). Like in the original analyses, we find that enforcing ALMPs weaken the relation between low literacy and long-term NEET versus being in education/training. In contrast with the original analyses, the interaction term is also significant for the specification of long-term NEET versus being employed.

Lastly, we re-estimated the analyses by leaving out one single country at the time. This does not change our main conclusions (results available on request).

2.6 LIMITATIONS

Before discussing our findings and drawing conclusions, it is good to note some shortcomings of our analyses. First, PIAAC is a cross-sectional survey, with all the limitations that are associated with that. One problem, for example, is that literacy skills are measured at the time of the interview, while skill levels may change during periods of inactivity. When young people are neither in employment nor in education/training, their skills may erode through lack of practice (OECD, 2012a). This depreciation of human capital increases over time (OECD, 2012a) and may lead to reverse causality (NEET status affecting the skills levels instead of the other way around). We see this as a main limitation to our analyses.

Second, an ideal data set would have allowed to compare changes within a country on the relation between literacy skills and NEET. This would require not only historical data regarding changes in the institutional characteristics in a country, but also individual level data on an individual's propensity to become NEET before and after such changes. Such a combination of time series data within and across countries is a very powerful tool to analyse the effect of policy interventions. Unfortunately, these data do not exist yet.

Third, our study was subject to some noteworthy data limitations. We were unable to distinguish the months of NEET as a linear dependent variable, as the PIAAC survey did not ask for the duration of NEET. We therefore decided to focus on young people who were NEET for at least one year, since the long-term scarring effect will be most prevalent in that group. However, a more dynamic approach to

being NEET would have been better (e.g., Brzinsky-Fay, 2007; Contini, Filandri & Pacelli, 2019; Dicks, Levels & Van der Velden, 2020; Levels et al., 2022). Furthermore, the NEET concept is rather criticized for being inherently vague (Levels et al., 2022) and for lumping together groups that are quite different, e.g., young people that have disillusioned withdrawn from the labour market to young adults taking a gap year after successfully finishing their studies. Unfortunately, the PIAAC data do not allow to further distinguish the group of NEETs. By focusing on the long-term NEETs (i.e., those in NEET status for 12 months or more), we hope to at least cover the ‘hard-core’ of the group.

Fourth, while young people entered the labour market at different times, the education system measure for vocational orientation and the measures on (enabling and enforcing) ALMPs are not time-varying. The issue here is that valid and reliable time-varying measures do not exist. We assume that this is not a problem because the macro-variation in the countries under study changes slowly and the ranking is unlikely to have changed. Follow-up research, for example on single countries, should focus on institutional reforms to confirm our results.

2.7 CONCLUSIONS & DISCUSSION

In this chapter we aim to explain the extent to which the likelihood that vulnerable young people with low literacy skills become socioeconomically marginalized as long-term NEET, and how this can be explained by countries’ education and social policies. We study young people aged 20-30 and use PIAAC data from 25 advanced countries. Multinomial analyses are performed to test whether young people are long-term NEET rather than being employed or being in education or training.

Our results indicate that young people with low literacy skills are caught in a “low skills trap”. Although the strength of the association differs across countries, we find that young people with low literacy skills are more likely to be long-term NEET. Reasons for this could be related to having more difficulties in acquiring and developing skills, which also makes them less likely to engage in training or further schooling. This is likely to be exacerbated as long-term inactivity can lead to further skills obsolescence (Mincer & Ofek, 1982; Bynner & Parsons, 1998; Salthouse, 2006; Desjardins & Warnke, 2012). This makes them more likely to leave education and try to find a job. However, having low literacy skills also decreases the chances on the labour market (Barrett, 2012) because employers always strive for the best possible match, given their preferences, opportunities and constraints (Kalleberg & Sorensen, 1979; Thurow, 1975; Sørensen & Kalleberg, 1981; Logan, 1996; Müller, 2005). Since people learn most from activities in education or at work, when such possibilities are being denied, low-literate NEETs have more difficulty in further developing

their skills. Therefore, low-literate NEETs find themselves in a trap from which it is increasingly difficult to escape.

Institutional characteristics might play a role in preventing low-literate young people from being caught in this trap. Their effectiveness in doing so is what this chapter has tried to assess. We expected that most of the institutional characteristics under study would weaken the odds for low-literate young people to become NEET. The main finding of this chapter is that this is not the case.

Just to be clear, the institutional characteristics that we looked at are systematically related to young people's general risk of becoming long-term NEET. Countries with high levels of (enabling) ALMPs seem more successful in keeping young people in education or training and preventing them from long NEET spells. However, these characteristics do not seem particularly helpful for the most vulnerable group: young people with low literacy skills. Rather the opposite: (enabling) ALMPs work in favour of young people with the highest literacy skills. The same holds when we look at different types of welfare states. Here we find that young people living in social-democratic welfare states are more likely to find themselves in employment or education/training than in a NEET position. However, we did not find evidence that this also holds specifically for low-literate young people. Again, the protective measures do not seem to be targeted towards the most vulnerable group. The only exception to this rule, was when we looked at enforcing ALMPs: These seem to work more in favour of young people with low literacy skills than for those with high literacy skills. However, given the overall negative effect of enforcing ALMPs on young people's risk to be pushed out of the education system and become NEET, this is not the kind of social policy a country would probably like to engage in.

So what does this imply for possible policy interventions? Concerns about NEETs and interventions to improve young people's integration in society (be it in education or on the labour market) figure high on national and international policy agendas (Eurofound, 2017), but little is known about interventions that specifically focus on the low-literate group (Windisch, 2015). When we look at our results, we note that most of the social policies to combat NEET are aimed at the mainstream group: young people with higher literacy skills. This is probably the case because it is easier to provide education, training or jobs to the group of higher-literate young people than to young people with lower literacy skills. If the policy aim is to reduce the overall number of NEETs in a country (and that is often the case (Eurofound, 2017)), the higher-skilled NEETs are the low-hanging fruit that will be picked first. It is much more difficult to help young people with low literacy skills, because such interventions can only be effective if they are linked to improving those persons' literacy skills. In addition, low-literate young people are difficult to reach. For example, the German campaign *Nur Mut - der nächste Schritt lohnt sich. Besser lesen und schreiben lernen* ("Take courage – the next step will pay off. Improve your reading and writing skills") used posters, TV and radio commercials to reach out to adults with low literacy

skills. While the campaign helped to raise awareness on low-literacy issues, it failed to reach the low-literate people themselves (OECD, 2019b). This problem may also have hampered the effectiveness of the education and social policy characteristics we studied in this chapter. For example, while ALMPs may seem to focus on young people at risk, the policies are often not designed specifically for groups at risk, particularly if they are low-literate young people (Pawson & Tilley, 1997; Vooren, Haelermans, Groot & Maassen van den Brink, 2019). This increases the risk of ALMPs failing to reach low-literate young people, thereby increasing the inequality between low- and high-literate groups. Therefore, policies should first focus on improving literacy skill levels among young people. Skills policies should start in primary and secondary education, so that young people will have gathered sufficient skills during the period of mandatory schooling. This is not only important for their educational and labour market success, but also for other daily tasks in life. If they are able to acquire better literacy skills, then education and social policy can further ensure that they can perform better in their economic and social participation in the society.

Nevertheless, a group of young people with low literacy skills will remain and at some point, they will leave education. It is essential for this group that social policy is much more targeted, actively reaching out, and creating awareness about the implications of having low literacy skills. This should not only be focused on the target group itself, but also on (prospective) employers. While providing additional opportunities for this group to follow education and training, much more should be done to foster skills development at work. For example, a Dutch programme entitled *Tel mee met Taal* offers subsidies encouraging employers to support low-literate employees with extra training (Bersee, 2019). Additionally, more attention should be paid to the evaluation of initiatives to promote the effectiveness of such programmes. Randomized control trials could be carried out to evaluate the effects of incentives to support low-literate young people before an approach is widely implemented.

2.8 REFERENCES

- Arts, W., and J. Gelissen. 2002. Three worlds of welfare capitalism or more? *Journal of European Social Policy*, 12(2):137-158.
- Audas, R., & Willms, J. D. (2001). *Engagement and dropping out of school: A life-course perspective*. Applied Research Branch, Strategic Policy, Human Resources Development Canada.
- Avvisati, F., & Kessler, F. (2014). REPEAT: Stata module to run estimations with weighted replicate samples and plausible values (Version 06 Jan 2020). *Statistical Software Components: Boston College Department of Economics*.
- Barrett, G. (2012). The Return to Cognitive Skills in the Australian Labour Market. *Economic Record*, 88(280), 1-17.
- Bersee, T. (2019). Een nieuw plan in de eeuwigdurende strijd tegen laaggeletterdheid. *Sociaal Bestek*, 81, 16-18.
- Bol, T., & Van de Werfhorst, H. G. (2011). Signals and closure by degrees: The education effect across 15 European countries. *Research in Social Stratification and Mobility*, 29(1), 119-132.
- Bol, T., & Van de Werfhorst, H. G. (2014). Educational Systems Dataset, version 4. Retrieved 17 February 2020, from <http://thijsbol.com/data>
- Bol, T., & Van de Werfhorst, H. G. (2016). Measuring educational institutional diversity: Tracking, vocational orientation and standardisation. In A. Hadjar & C. Gross (Eds.), *Education systems and inequalities: International comparisons*. Bristol: Bristol University Press, 73-94.
- Breen, R. (2005). Explaining cross-national variation in youth unemployment: Market and institutional factors. *European Sociological Review*, 21(2), 125-134.
- Brzinsky-Fay, C. (2007). Lost in transition? Labour market entry sequences of school leavers in Europe. *European Sociological Review*, 23(4), 409-422.
- Bynner, J., & Parsons, S. (1998). *Use it or Lose it? The impact of time out of work on literacy and numeracy skills*. London: ERIC.
- Cairns, R. B., Cairns, B. D., & Neckerman, H. J. (1989). Early school dropout: Configurations and determinants. *Child development*, 60, 1437-1452.
- Cassen, R., & Kingdon, G. (2007). *Tackling low educational achievement*. London, UK: Joseph Rowntree Foundation.
- Coles, B., Hutton, S., Bradshaw, J., Craig, G., Godfrey, C., & Johnson, J. (2002). *Literature review of the costs of being "not in education, employment or training" at age 16-18*. Department of Education and Skills, RR 346. DfES Publications: Nottingham.
- Contini, D., Filandri, M., & Pacelli, L. (2019). Persistency in the NEET state: A longitudinal analysis. *Journal of youth studies*, 22(7), 959-980.
- Desjardins, R., & Warnke, A. J. (2012). Ageing and skills: A review and analysis of skill gain and skill loss over the lifespan and over time. *OECD Education Working Papers*, No. 72.
- Dicks, A., Levels, M., & Van der Velden, R. (2020). From school to where? How social class, skills aspirations, and resilience explain unsuccessful school-to-work transitions. *ROA Research Memorandum*, No. 013.

- Dingeldey, I. (2007). Between workfare and enablement: The different paths to transformation of the welfare state: A comparative analysis of activating labour market policies. *European Journal of political research*, 46(6), 823-851.
- Esping-Andersen, G. (1990). *The three worlds of welfare capitalism*. Cambridge: Polity Press.
- Eurofound. (2012). *NEETs - Young people not in employment, education or training: Characteristics, costs and policy responses in Europe*. Luxembourg: Publications Office of the European Union.
- Eurofound. (2017). *Long-term unemployed youth: Characteristics and policy responses*. Luxembourg: Publications Office of the European Union.
- Fan, W., & Wolters, C. A. (2014). School motivation and high school dropout: The mediating role of educational expectation. *British Journal of Educational Psychology*, 84(1), 22-39.
- Ferrera, M. (1996). The 'Southern Model' of Welfare in Social Europe. *Journal of European Social Policy* 6(1), 17-37.
- Ferrera, M., & Rhodes, M. (2000). Recasting European welfare states: An introduction. *West European Politics*, 23(2), 1-10.
- Finnie, R., & Meng, R. (2001). Cognitive skills and the youth labour market. *Applied Economics Letters*, 8(10), 675-679.
- Gal, J. (2010). Is there an extended family of Mediterranean welfare states? *Journal of European Social Policy*, 20(4), 283-300.
- Gallie, D., & Paugam, S. (2000). *Welfare regimes and the experience of unemployment in Europe*. Oxford: Oxford University Press.
- Gebel, M., & Giesecke, J. (2011). Labor market flexibility and inequality: The changing skill-based temporary employment and unemployment risks in Europe. *Social Forces*, 90(1), 17-39.
- Gebel, M., & Giesecke, J. (2016). Does deregulation help? The impact of employment protection reforms on youths' unemployment and temporary employment risks in Europe. *European Sociological Review*, 32(4), 486-500.
- Gladwell, D., Popli, G., & Tsuchiya, A. (2016). A dynamic analysis of skill formation and NEET status. *Sheffield Economic Research Paper Series. SERPS*(2015016).
- Hadjivassiliou, K. P., Tassinari, A., Eichhorst, W., & Wozny, F. (2016). Assessing the performance of school-to-work transition regimes in the EU. *IZA Discussion Papers*, No. 10301.
- Hernandez, D. J. (2011). *Double jeopardy: How third-grade reading skills and poverty influence high school graduation*. Baltimor, MD: Annie E. Casey Foundation.
- Hodkinson, P. (1996). Careership: the individual, choices and markets in the transition to work. In J. Avis, M. Bloomer, G. Esland, D. Gleeson, & P. Hodkinson (Eds.), *Knowledge and nationhood: Education, politics and work* (pp. 121-139). London: Continuum.
- Hodkinson, P., & Sparkes, A. C. (1997). Careership: A sociological theory of career decision making. *British journal of sociology of education*, 18(1), 29-44.
- Iannelli, C., & Raffe, D. (2007). Vocational upper-secondary education and the transition from school. *European Sociological Review*, 23(1), 49-63.
- Jongbloed, J., and Giret, J.-F. (2021). Quality of life of NEET youth in comparative perspective: 3. subjective well-being during the transition to adulthood. *Journal of Youth Studies*, 25(3), 321-343.

- Kalleberg, A. L., & Sorensen, A. B. (1979). The sociology of labor markets. *Annual review of sociology*, 5(1), 351-379.
- Knotz, C. M. (2012). Measuring the 'new balance of rights and responsibilities' in labor market policy: A quantitative overview of activation strategies in 20 OECD countries. *ZeS-Working Paper*, No. 06/2012.
- Kogan, I., & Müller, W. (2003). *School-to-work transitions in Europe: Analyses of the EU LFS 2000 ad hoc module*. Mannheim: Mannheimer Zentrum für Europäische Sozialforschung.
- Leuven, E., Oosterbeek, H., & Van Ophem, H. (2004). Explaining international differences in male skill wage differentials by differences in demand and supply of skill. *The Economic Journal*, 114(495), 466-486.
- Levels, M., Brzinsky-Fay, C., Holmes, C., Jongbloed, J., & Taki, H. (2022). *The dynamics of marginalized youth: Not in education, employment, or training around the world*. London: Routledge.
- Levels, M., Van der Velden, R., & Allen, J. (2014). Educational mismatches and skills: New empirical tests of old hypotheses. *Oxford Economic Papers*, 66(4), 959-982.
- Levels, M., Van der Velden, R., & Di Stasio, V. (2014). From school to fitting work: How education-to-job matching of European school leavers is related to educational system characteristics. *Acta Sociologica*, 57(4), 341-361.
- Logan, J. A. (1996). Opportunity and choice in socially structured labor markets. *American Journal of Sociology*, 102(1), 114-160.
- Mincer, J. (1974). *Schooling, experience, and earnings*. New York: National Bureau of Economic Research.
- Mincer, J., & Ofek, H. (1982). Interrupted work careers: Depreciation and restoration of human capital. *Journal of human Resources*, 17(1), 3-24.
- Müller, W. (2005). Education and youth integration into European labour markets. *International Journal of Comparative Sociology*, 46(5-6), 461-485.
- OECD. (2011). *PIAAC conceptual frame-work of the background questionnaire main survey*. Paris: OECD Publishing.
- OECD. (2012a). *Better skills, better jobs, better lives: A strategic approach to skills policies*. Paris: OECD Publishing.
- OECD. (2012b). *Literacy, Numeracy and Problem Solving in Technology-Rich Environments Framework for the OECD survey of Adult Skills*. Paris: OECD Publishing.
- OECD. (2013a). *OECD Skills Outlook 2013: First results from the survey of adult skills*. Paris: OECD Publishing.
- OECD. (2013b). *PIAAC data*.
- OECD. (2015). *OECD Skills Outlook 2015: Youth, skills and employability*. Paris: OECD Publishing.
- OECD. (2016). *Technical Report of the Survey of Adult Skills (PIAAC) - 2nd Edition*. Paris: OECD Publishing.
- OECD. (2018). *Education at a Glance 2018: OECD indicators*. Paris: OECD Publishing.

- OECD. (2019a). Economic Outlook No 105 - May 2019: Output gaps: deviations of actual GDP from potential GDP as % of potential GDP. Retrieved 11 October 2019, from <https://stats.oecd.org/index.aspx?queryid=51655>
- OECD. (2019b). *Getting Skills Right: Engaging low-skilled adults in learning*. Paris: OECD Publishing.
- OECD. (2020a). Youth not in employment, education or training (NEET) (indicator). Retrieved 13 October 2019, from <https://data.oecd.org/youthinac/youth-not-in-employment-education-or-training-neet.htm>
- OECD. (2020b). Public expenditure and participant stocks on LMP (Active measures). Retrieved 17 February 2020, from <https://stats.oecd.org/index.aspx?DataSetCode=LMPEXP#%20>
- Pastore, F. (2018). Why is youth unemployment so high and different across countries? *IZA World of Labor*.
- Pawson, R., & Tilley, N. (1997). *Realistic evaluation*. London: Sage.
- Pohl, A., & Walther, A. (2007). Activating the disadvantaged: Variations in addressing youth transitions across Europe. *International Journal of Lifelong Education*, 26(5), 533-553.
- Rudd, R., Kirsch, I., & Yamamoto, K. (2004). *Literacy and health in America. Policy information report*. Princeton: Educational Testing Service.
- Ryan, P. (2001). The school-to-work transition: A cross-national perspective. *Journal of economic literature*, 39(1), 34-92.
- Salthouse, T. A. (2006). Mental exercise and mental aging: Evaluating the validity of the “use it or lose it” hypothesis. *Perspectives on Psychological Science*, 1(1), 68-87.
- Shavit, Y., & Müller, W. (2000). Vocational secondary education: Where diversion and where safety net? *European Societies*, 2(1), 29-50.
- Social Exclusion Task Force. (2008). *Think family: Improving the life chances of families at risk*. London: Cabinet Office.
- Solga, H. (2002). Stigmatization by negative selection: Explaining less-educated people's decreasing employment opportunities. *European Sociological Review*, 18(2), 159-178.
- Sørensen, A. B., & Kalleberg, A. L. (1981). An Outline of a Theory of Matching Persons to Jobs. In I. Berg (Ed.), *Sociological Perspectives on Labor Markets* (pp. 49-74). New York: Academic Press.
- Strelitz, J., & Darton, D. (2003). Tackling disadvantage: Place in Darton. In D. Darton & J. Strelitz (Eds.), *Tackling UK poverty and disadvantage in the twenty-first century: An exploration of the issues*. York: Joseph Rowntree Foundation.
- Thurow, L. C. (1975). *Generating inequality: Mechanisms of distribution in the U.S. economy*. New York: Basic Books.
- Traag, T., & Van der Velden, R. (2011). Early school-leaving in the Netherlands: The role of family resources, school composition and background characteristics in early school-leaving in lower secondary education. *Irish Educational Studies*, 30(1), 45-62.
- Van de Werfhorst, H. G. (2011). Skill and education effects on earnings in 18 countries: The role of national educational institutions. *Social Science Research*, 40(4), 1078-1090.
- Van der Velden, R, Wolbers, M. (2003), The integration of young People into the Labour market: The role of training systems and labour market regulation, In: W. Müller, M. Gangl (Eds.),

- Transitions from education to work in Europe: The integration of youth into EU labour markets* (pp. 186-211). Oxford: Oxford University Press.
- Vooren, M., Haelermans, C., Groot, W., & Maassen van den Brink, H. (2019). The effectiveness of active labor market policies: A meta-analysis. *Journal of Economic Surveys*, 33(1), 125-149.
- Walther, A. (2006). Regimes of youth transitions: Choice, flexibility and security in young people's experiences across different European contexts. *Young*, 14(2), 119-139.
- Windisch, H. C. (2015). Adults with low literacy and numeracy skills. *OECD Education Working Papers*, No. 123.

3

THE EFFECT OF PUBLIC CHILDCARE ON THE RISK THAT MOTHERS BECOME NEET

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3.1 ABSTRACT

This chapter explores to what extent the risk that young mothers become NEET (Not in Employment, Education or Training) is related to the costs of family policy provisions (Early Childhood Education and Care). Young women are much more likely to be NEET than young men. Little is known to what extent institutional and policy contexts can shape the relationship between young motherhood and NEET – in particular with respect to the potential role of family policy. We combine data from the EU-LFS with macro-level indicators of family policies, and analyse NEET risks of 13,737 young mothers (20-29) in 22 EU-countries. Results suggest that there is a link between costs of childcare and the likelihood to become NEET for young mothers across the EU. The mechanisms behind this relationship show that the costs of childcare are related to the use of ECEC and that the use of ECEC is related to subsequent NEET risks. Results are robust to the Oster bound approach.

3.2 INTRODUCTION

Young women are much more likely to be Not in Employment, Education or Training [NEET] than young men (Carcillo, Fernández, Königs, & Minea, 2015; Eurofound, 2012, 2016; OECD, 2019b). Being NEET negatively affects women's later labour market outcomes, but it is also associated with early marriage or cohabiting, feelings of dissatisfaction with life, lack of a sense of control, and experiencing problems in life (Bynner & Parsons, 2002). Research on contextual explanations for NEET risks focuses on educational systems and labour market characteristics, but less is known about institutional and policy contexts that specifically shape the relationship between young motherhood and NEET – in particular with respect to the potential role of family policy.

In this chapter, we study to what extent the affordability of Early Childhood Education and Care (ECEC) can explain whether young mothers become NEET in different European countries. We specifically focus on the role of motherhood, as motherhood continues to be one of the main explanations of women's lower labour market participation rates (Goldin, 2014; Van der Lippe & Van Dijk, 2002), and on ECEC as a key family policy that supports maternal employment (Olivetti & Petrongolo, 2017).

We use data from the European Union Labour Force Survey (EU-LFS), covering 27 countries with the 2010 ad-hoc module 'Reconciliation between work and family life'. An advantage of the EU-LFS is that this dataset provides sufficiently large samples to examine the sub-group of NEETs across European countries, and the ad hoc module pays special attention to work-related questions after childbirth such as the use of childcare. We complement these data with macro data about the affordability of public childcare across European countries from MultiLinks, OECD, and the OECD family database. We use these data to establish the association between ECEC affordability and NEET rates among young mothers, and to demonstrate the mechanisms that drive this association. We do this by observing two probabilities which are important for understanding how motherhood links to NEET, i.e. the probability that young mothers use public childcare services, and the probability that young mothers who use these services become NEETs.

We exploit cross-country variation in early childcare provision. This variation is exogenous to inhabitants of these countries. However, across countries, both the likelihood to be NEET and the use of early childcare may be related to other country characteristics. For instance, in wealthier countries, the likelihood to be NEET may be lower, while such countries may at the same time also be able to offer more affordable public childcare. Not controlling for country wealth would then attribute the effect of wealth on NEET to the effect of early childcare provision on NEET, i.e. the estimate of the effect of early childcare provision on NEET would be biased. While we control for several important country characteristics, it remains possible that the estimated

relationship is biased due to omitted variables. We address this concern by providing lower and upper bounds of the estimates using the approach proposed by Oster (2019).

The following research questions are distinguished: *To what extent do policies that determine the affordability of public childcare (national-level) affect childcare use by young mothers? To what extent does individual-level use of ECEC reduce young mother's NEET risks?*

This research complements and extends previous research in the following ways. First, it adds to the literature on NEETs by examining NEET as a gendered phenomenon, by introducing a focus on motherhood and family policies as important determinants (Levels, Brzinsky-Fay, Holmes, Jongbloed, & Taki, 2022). Second, we add to the literature by dissecting the mechanisms through which public childcare services are correlated with young mothers' participation in the labour market and in education. Lastly, to gain insight into the importance of omitted variable bias, our analyses are among the first to use the methodology proposed by Oster (2019) in this context.

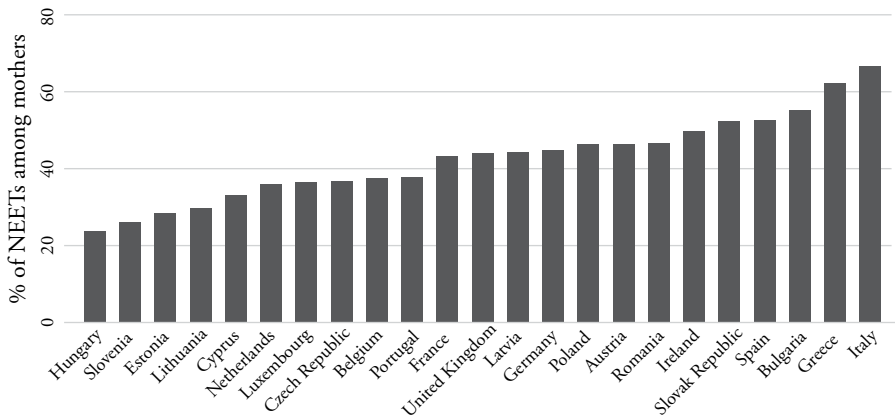
Examining NEET as a gendered phenomenon with a focus on the potential role of motherhood has important policy implications. Current NEET policies are mainly concerned with helping people return to work or school (European Commission, 2010). However, support for labour market (re-)engagement without affordable childcare may not help NEETs who have a child. Therefore, it could be more important to look at family-related policies rather than general labour market policies when examining the relationship between young motherhood and the risk of becoming NEET.

The set-up of this chapter is as follows. In the next section, we give background statistics on the likelihood to be NEET across countries in the European Union, followed by a section in which we develop the theoretical framework. This is followed by sections that introduce the data, and that explain the empirical strategy. After this, the results are presented, and the final section concludes.

3.3 THEORY & HYPOTHESES

Young mothers on average have a higher risk of being NEET than women without children (Levels et al., 2022). Figure 3.1 shows the percentage of young mothers who are NEET across European countries. The average percentage of NEETs among young mothers in the European Union (EU) is 46.7% and ranges from 23.7% in Hungary to 66.7% in Italy.

Several types of explanations are commonly suggested for this cross-national variation. First, compositional population differences (such as educational and socio-economic background) might explain the cross-national variation of NEET risks (Eurofound, 2012, 2016). Second, contextual differences pertaining to laws, institutions and policies may play a role.



Note: This figure is based on our own calculations from the EU-LFS 2010. More detailed information about the dataset can be found in the data-section.

Figure 3.1 - Percentage of NEETs among young mothers in the EU (2010)

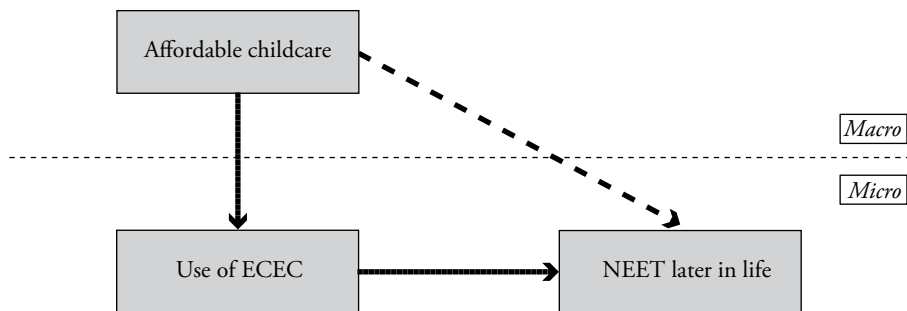
Family policies are a third potential explanation for this variation, as these policies are known to relate to how likely mothers (re-)enter the labour market (Nieuwenhuis, Need, & Van der Kolk, 2012; Pettit & Hook, 2005). Family policies can reduce the likelihood that young mothers become NEET by decreasing the distance to the labour market by offering parental leave benefits or childcare services. Childcare services are considered among the most important family policy measures to increase maternal employment (Olivetti & Petrongolo, 2017). However, family policies can also affect earlier decision-making. For example, they can influence young mothers' decisions to drop out of school or stop working before or immediately after childbirth.

Our main argument why childcare provision is related to NEET is that time devoted to parental obligations, particularly with respect to young children, cannot be spent on work or education. The use of public childcare may facilitate young mothers to combine motherhood with employment, education or training. Yet, the likelihood that young mothers use childcare depends on a number of institutional factors, most notably its affordability. The affordability of public childcare differs widely between countries (Thévenon, 2011; Thévenon & Luci, 2012). Our main hypothesis is:

In countries where ECEC is more affordable, young mothers are less likely to become NEET than in countries where ECEC is less affordable (Hypothesis 1).

3.3.1 Expected mechanisms underlying childcare costs and NEET risks

To understand how variation across countries in childcare affordability is related to NEET risks among young mothers, we examine mechanisms potentially underlying this relationship. We distinguish two stages: (1) the extent to which the (national-level) affordability of public childcare is associated with its use by young mothers, and (2) whether individual-level use of childcare helps young mothers reduce NEET risks. These stages are illustrated in Figure 3.2.



Note: the solid arrows show the expected mechanisms underlying the relationship between affordable childcare and NEET risks later in life

Figure 3.2 - Visual overview of stages that describe how childcare (ECEC) can be associated with NEET risks (among young mothers)

Young mothers (and their partners) have to allocate time otherwise spent being active on the labour market or in education to child-rearing. We assume that when making the decision about how to allocate time, women and their partners compare costs and benefits of the various options, preferring less costly options over more costly ones (Becker, 1965, 1981). All else being equal, we assume that young women and their partners are more likely to use ECEC if using these policies is less costly. Therefore, we expect that lower costs of ECEC will be related to a higher likelihood of families to make use of ECEC. Our hypothesis is:

Young mothers are more likely to use ECEC in countries where ECEC is more affordable compared to countries where ECEC is less affordable (Hypothesis 2).

We also expect that young parents make a trade-off between the use of ECEC and the time not spent in employment or education. The time devoted to taking care of children limits the time spent in the labour force or education. When young mothers use ECEC, they can reconsider their balance between work/education and family life.

A benefit of using ECEC is that young mothers are more able – and thus more likely – to continue working (OECD, 2011) or studying. Therefore, we hypothesise:

Young mothers who use ECEC have lower NEET risks than young mothers who do not use ECEC (Hypothesis 3).

3

3.4 DATA, MEASUREMENTS & METHODS

3.4.1 Data

The European Union Labour Force Survey (EU-LFS) is a large cross-country household survey on labour market participation conducted in 28 EU member states, as well as Iceland, Norway and Switzerland. We use data from 2010, including the 2010 ad hoc module ‘Reconciliation between work and family life’ with specific topical data on work and care related questions after childbirth. Furthermore, we use macro-data from MultiLinks, OECD and the OECD family database to assess the ECEC affordability but also to control for various country characteristics.

To test our hypotheses, we select young mothers aged 20-29 whose youngest child is born after 2004 and lives within the household. This age-range is chosen because until age 19 most young people are in compulsory education (OECD, 2018) and the upper age (29 years old) is chosen to be consistent with the NEET indicator of the OECD (OECD, 2020). In addition, the average age of mothers having their first child is 30 in the EU, which means that mothers who give birth earlier are relatively young mothers (Eurostat, 2022). We removed Malta and Croatia because of the low number of young mothers in the dataset. Nordic countries (Denmark, Finland, Norway and Sweden) are also excluded from our sample because there is no information on the birth year of the (youngest) child. We also delete cases with missing values on the variable ECEC use ($N=93$). This results in a working sample of $N=13,819$ young mothers from 23 countries with a child living in the household below age 7. For the analyses presented in Table 3.2, Table 3.3 and Table 3.4, we additionally exclude Cyprus because of missing data on childcare costs. This results in a working sample of $N=13,737$ young mothers aged 20-29 from 22 countries. However, we start our results with a description of whether there is a significant relationship between young motherhood and subsequent NEET risk per country. For this, we also included young women who did not have a child ($N=64,289$).

Descriptive statistics of all variables are presented in Table 3.1. We describe how the variables are measured below.

3.4.2 Measurements

Individual-level variables

The binary dependent variable *NEET* is (1) when mothers are unemployed, in retirement or early retirement or have given up a business, are permanently disabled, fulfil domestic tasks or have other inactivity reasons, and (0) otherwise. The main activity status was not asked in Germany or the United Kingdom. Therefore, we constructed the NEET status based on ILO work status and education status. Here, we label young mothers as NEET if they were not in education or an apprenticeship in the last 4 weeks before the survey, and not in employment during the reference week.

Use of ECEC is a dummy variable, which is (1) when young mothers used formal childcare services (including paid childminders, pre-school, apart from compulsory school) for their youngest child, and (0) in all other cases.

Furthermore, in our models we control for *education level* in three categories: low (no formal education, ISCED 1 and 2), medium (ISCED 3 and 4) and high (ISCED 5 and 6); *age* (20-24 years versus 25-29 years); and *migration background* (native versus non-native). The first mentioned categories are the reference categories.

Country-level variables

We include a number of country-level variables. Our main interest is in the *childcare costs*. These costs are defined as net childcare costs (after benefits) paid by single persons with two children for full-time centre-based childcare, expressed as a percentage of their disposable household income (OECD, 2019a). These data are available for the years 2004, 2008 and 2012. To allow time-variation and differences across all birth years of the youngest child, the years in between are included by a linear interpolation.

In addition, we include theory-informed control variables. First, we control for other family policies: the *duration of maternity leave* and *parental leave*. These are important because the longer mothers are on leave, the less likely they are to use childcare. Secondly, we control for a number of political determinants that shape childcare policy differences across countries. We select these determinants based on Bonoli and Reber (2010), who show that childcare policies are more generous in countries with a larger share of seats in parliament held by women, and a smaller share of seats in parliaments held by religious parties. Finally, we control for a number of labour market conditions that might affect NEET risks: the overall unemployment rate and the GDP per capita. These variables are defined in detail below.

Maternity leave: Average duration of maternity leave (Weeks) (Multilinks, 2011). These data are available for each country for the years 2004 and 2009. To allow time-variation and differences across all birth years of the youngest child, the years in between are included by a linear interpolation; the year 2010 is copied from the year 2009.

Parental leave: The available parental leave benefit measured in average length of payment (Months) (Multilinks, 2011). These data are available for each country for the years 2004 and 2009. To allow time-variation and differences across all birth years of the youngest child, the years in between are included by a linear interpolation; the year 2010 is copied from the year 2009.

Seats women in parliament: Proportion of seats held by women in national parliaments (%) (Teorell et al., 2022). These data are available for all countries and for all the birth years (2005-2010) that are used in the analyses.

Seats religious parties in parliament: Share of seats in national parliament held by religious parties (%) (Teorell et al., 2022). These data are available for all countries and all the birth years (2005-2010) that are used in the analyses.

Unemployment rate (2010): The percentage of unemployed people within the labour force population (OECD, 2019c). Since the NEET-status is measured in 2010, we include only the unemployment rate of 2010.

GDP: Gross Domestic Product in US dollar/capita (OECD, 2022). These data are available for all countries and all the birth years (2005-2010) that are used in the analyses.

All our country-level variables are standardized.

Table 3.1 - Descriptive statistics

	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>
<i>Individual-level variables</i>					
NEET (EET=ref.)	13,737	0.47		0.00	1.00
Use of ECEC (No=ref.)	13,737	0.26		0.00	1.00
Education level (Low=ref.)	13,737	0.30		0.00	1.00
Medium	13,737	0.52		0.00	1.00
High	13,737	0.18		0.00	1.00
Age (Age 25-29=ref.)	13,737	0.28		0.00	1.00
Age 25-29	13,737	0.72		0.00	1.00
Migration background (Native=ref.)	13,737	0.16		0.00	1.00
<i>Country-level variables</i>					
Net childcare costs - single hh	22	-0.02	0.99	-1.64	2.78
Maternity leave (Weeks)	22	0.03	1.02	-1.03	3.23
Paid parental leave (Months)	22	0.02	1.00	-0.88	1.87
Unemployment rate (2010)	22	0.05	0.95	-1.35	2.34
GDP	22	0.58	0.96	-1.21	5.99
Seats women in parliament	22	0.15	0.99	-1.33	2.67
Seats religious in parliament	22	-0.06	0.97	-0.71	2.60

3.4.3 Methods

To test our hypotheses, we estimate the following model:

$$NEET_{ic} = ECEC_c \alpha + X_i \beta' + X_c \gamma' + \varepsilon_{ic}, \quad (1)$$

where $NEET_{ic}$ is a dummy variable which is one if mother i in country c is NEET (not employed, in education, or training). Our main independent variable is the costs of early childcare provision ECEC. The effect of these costs on the likelihood to be NEET is captured by α . In each of our models, we control for a vector of individual characteristics X_i which includes the mother's level of education, age, and migration background. The effect of these characteristics on the likelihood to be NEET is captured by the vector β' . X_c is a vector of variables at the country-level.

In model 2, these include maternity leave and paid parental leave. In model 3, these additionally include GDP, seats of women in parliament, and seats of religious parties in parliament. Their effects on the likelihood to be NEET are captured by the vector γ' . Note that adding more variables reduces the degrees of freedom, so especially in Model 3 the estimates will be less efficient.

We use Linear Probability Model regressions, and cluster standard errors at the country level allowing observations to be correlated within countries, but not between countries.⁷

Assessing potential omitted variable bias

To control for unobserved heterogeneity, we run additional analyses, using the methodology proposed by Oster (2019) in which we estimate the bias that arises from omitting important influences on the ECEC services. This method starts by evaluating the robustness of the coefficient of our most important independent variable after controls are added to the model, in combination with the increase in the R-squared due to the addition of these control variables to the model. If the coefficient is rather stable while the R-squared increases, this method basically infers that the coefficient will also remain stable if other important variables would be included in the model. Given assumptions about the maximum R-squared that can be reached, the method can indicate the largest possible change in the main coefficient, i.e., it can provide bounds for this coefficient. The maximum R-squared is typically not set to unity because variables contain measurement error. Oster (2019) suggests using a maximum of 1.3, 2, and 3 times the R-squared of the model that contains all important controls.

Next, the model needs input on either (1) the assumed impact of the unobserved variables on the coefficient of interest relative to the impact of the observables (δ), or (2) the value of the coefficient (β). If the assumed impact of the unobserved variables on the coefficient of interest relative to the impact of the observables (δ)

⁷ While a multi-level analyses would also have been possible, the methodology proposed by Oster (2019) does not support this analytical design.

for instance equals one, the assumption is that the effect of the observables on the coefficient of interest is equal to the effect of the unobserved heterogeneity. If delta equals 0.5, the effect of unobserved variables is assumed to be half of the effect of the observables.

We focus on how large the coefficient of interest (beta) will be, given assumed values of the maximum R-squared and the impact of the unobserved variables on the coefficient of interest relative to the impact of the observables (delta). In other words, our output gives bounds of the coefficient. We show bounds using the standard maximum R-squareds of 1.3, 2, and 3 times the R-squared of the model that contains all important controls, and for delta set to 0 and 1.

3.5 RESULTS

Figure 3.3 shows the relationship between motherhood and subsequent NEET risk per country (Appendix B, Table B1). Across Europe, young mothers have higher NEET risks than women without children, although we observe large cross-national variation in how strongly motherhood and NEET risks are associated. The relationship between young motherhood and NEET risks is weakest in Slovenia, Lithuania and Latvia. Countries with relatively strong associations between young motherhood and subsequent NEET risks are Austria, Slovak Republic and Germany.

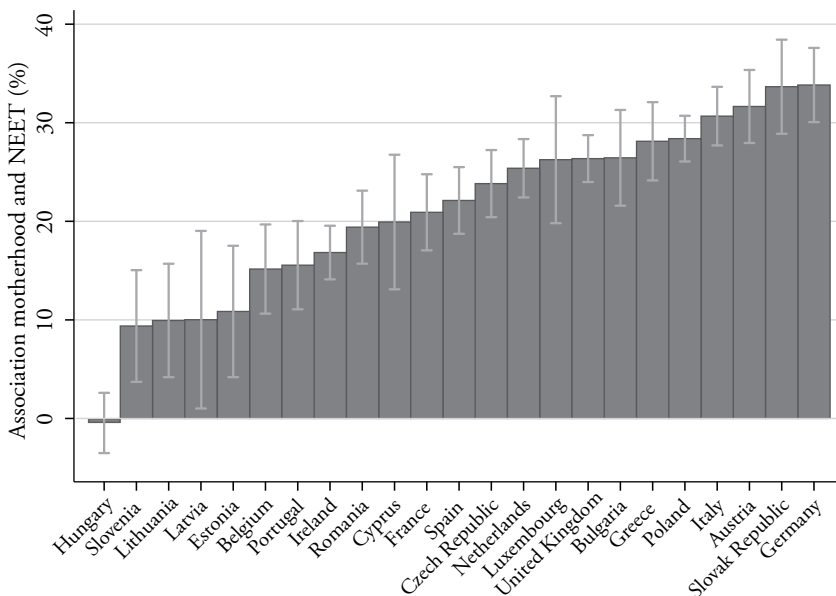


Figure 3.3 - Association between motherhood and subsequent NEET risks, controlled for age, education level and migration background

3.5.1 Costs of childcare and NEET risks

Table 3.2 shows the main result of our analysis. The table displays the relationship between the costs of childcare and the likelihood to become NEET. In Model 1, no control variables at the country-level are included; Model 2 includes the length of maternity leave (weeks) and the length of paid parental leave (months). Model 3 additionally controls for the unemployment rate, GDP, percentage of women in national parliament and percentage of religious seats taken in parliament.

In accordance with our expectations, all three models show that higher ECEC costs are related to a higher chance that young mothers become NEET. This relationship is sizable. A one standard deviation increase in ECEC costs is associated with a 4 percentage-points higher chance that young mothers become NEET. The direction of the relationship is robust to the inclusion of control variables, but the parameter is no longer statistically significant after including control variables at the country level. The latter could be due to the rather small sample size (22 countries) or imply that the relationship between ECEC costs and young mothers becoming NEET is mediated by the actual use of childcare which we will test in Hypothesis 2 and Hypothesis 3.

We present Oster bounds at the bottom of the table. For ease of comparison, the first row repeats the estimates the childcare costs (i.e. β when $\delta = 0$). Next, we analyse the bias adjusted Oster estimates (β^*) under the assumption that $\delta = 1$, and setting $R_{max} = 1.3\tilde{R}$, $R_{max} = 2.0\tilde{R}$ or $R_{max} = 3.0\tilde{R}$ respectively. We find that with higher R_{max} , the bias adjusted estimates of childcare costs are rising, and hence remain positive. This reduces concerns that omitted variables may drive the relationship we find between childcare costs and NEET to zero.

Based on the Oster estimates from Model 1, we can estimate the bounds of the relationship between childcare costs and NEET. The β of costs of childcare is 0.04 in Model 1 and the β when $\delta = 1$ and the maximum R-squared is three times the R-squared of the model that includes all controls is 0.10. Therefore, the estimated coefficient is between 0.04 and 0.10.

To add confidence intervals to these bounds, we need the standard errors of the Oster coefficients. These are not provided by the estimation technique but if they would be provided, these standard errors would be somewhat lower than the standard error of our variable of interest provided in Model 1. The reason is that including more control variables related to the main variable of interest will reduce the standard errors of this main variable (Wooldridge, 2013). Hence, we know that the standard error of our main coefficient provided in model 1 provides an upper limit of the standard error related to the Oster coefficients. Therefore, we can provide conservative confidence intervals using the standard errors of the main estimation in model 1 for the Oster bounds. Doing so, the conservative 95 percent confidence interval is -0.008 (0.044-1.96*0.018) and 0.133 (0.098+1.96*0.018).⁸ So we are 95 percent certain that one standard deviation higher costs of childcare is related to a 0.8-13.3 percentage-points

⁸ The calculations are based on the unrounded estimates in the figures.

higher likelihood to be NEET. This finding is in line with Hypothesis 1. However, it is no longer significant after including the control variables at the country level such as the length of maternity and parental leave.

Table 3.2 - Parameter estimates for the relationship between childcare costs and NEET, including Oster bounds

	M1	M2	M3
Net childcare costs - single hh	0.04* (0.02)	0.03 (0.02)	0.03 (0.03)
Education level (Low=ref.)			
Medium educated	-0.22*** (0.02)	-0.21*** (0.02)	-0.21*** (0.02)
High educated	-0.35*** (0.03)	-0.35*** (0.03)	-0.35*** (0.03)
Age 25-29 (Age 20-24=ref.)	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)
Migration background (Native=ref.)	0.14*** (0.04)	0.12*** (0.03)	0.13*** (0.03)
Maternity leave (Weeks)		0.00 (0.02)	0.00 (0.02)
Paid parental leave (Months)		-0.03 (0.03)	-0.04 (0.03)
Unemployment rate (2010)			-0.01 (0.01)
GDP			-0.01 (0.02)
Seats women in parliament			-0.00 (0.02)
Seats religious in parliament			0.00 (0.02)
Constant	1.08*** (0.11)	1.08*** (0.10)	1.09*** (0.09)
$\tilde{R}$ -squared	0.09	0.10	0.10
N young mothers	13,737	13,737	13,737
N country	22	22	22
<i>Oster Method:</i>			
β when $\delta = 0$	0.04	0.03	0.03
β when $\delta = 1$ and R_{max} is 1.3	0.05	0.04	0.05
β when $\delta = 1$ and R_{max} is 2.0	0.07	0.05	1.06
β when $\delta = 1$ and R_{max} is 3.0	0.10	0.09	4.04

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The following analyses describe the mechanisms behind the relationship of childcare costs and NEET risks.

3.5.2 Costs of childcare and use of ECEC

Table 3.3 shows the results for the relationship between the costs of childcare and the use of ECEC among young mothers. In Model 1, no control variables at the country-level are included; Model 2 includes the length of maternity leave (weeks) and the length of paid parental leave (months). Model 3 additionally controls for the unemployment rate, GDP, percentage of women in national parliament and percentage of religious seats taken in parliament.

In accordance with our expectations, all three models show that young mothers are more likely to use ECEC in countries where ECEC is more affordable compared to countries where ECEC is less affordable (Hypothesis 2). Note that in Model 3, where we control for most country-level variables, the relationship between childcare costs and the use of ECEC is strongest (from -0.05 in Model 1 to -0.09 in Model 3). This suggests that an increase of childcare costs with one standard deviation is associated with a decrease of 9 percentage-points in ECEC use (Model 3).

We present Oster bounds at the bottom of the table. We find that with higher *Rmax*, the bias-adjusted estimates of childcare costs are rising (in absolute sense), and hence remain negative under the three *Rmax* assumptions. This suggests there is little concern regarding omitted variable bias in these models for the relationship between childcare costs and the use of ECEC.

3.5.3 Use of ECEC and NEET risks

Table 3.4 reports the relationship between the use of ECEC by young mothers and their subsequent NEET risks. In Model 1, no country-level variables are included; Model 2 includes childcare costs; Model 3 adds the length of maternity leave (weeks) and the length of paid parental leave (months); Model 4 additionally controls for the unemployment rate, GDP, percentage of women in national parliament and percentage of religious seats taken in parliament.

Across all models in Table 3.4, we find support for our expectation: Young mothers who use ECEC have lower NEET risks than young mothers who do not use ECEC (Hypothesis 3). In all models, the estimates reveal that young mothers who use ECEC are approximately 22%-point less likely to become NEET compared to young mothers who do not use ECEC. Furthermore, note that none of the country-level variables is significantly associated with subsequent NEET risks, which means that the use of ECEC seems more important than country-specific factors in relation to NEET risks.

Across the four models, the coefficient remains very stable. This narrows the bounds we estimate with the Oster method. On the other hand, the R-squareds in the models presented in Table 3.4 are about 13%, indicating that the controls do not explain much of the variation in the dependent variable. This will increase the Oster bounds.

We present the bounds at the bottom of the table. We find that when assuming higher maximum values of the R-squared (R_{max}), the bias-adjusted estimates of childcare costs are getting smaller (in absolute sense), but remain negative. This suggests there is little concern regarding omitted variable bias in these models for the effect of childcare costs on the use of ECEC.

Table 3.3 - Parameter estimates for the relationship between childcare costs and use of ECEC, including Oster bounds

	M1	M2	M3
Net childcare costs - single hh	-0.05* (0.02)	-0.05* (0.02)	-0.09* (0.03)
Education level (Low=ref.)			
Medium educated	0.04* (0.02)	0.04* (0.02)	0.04* (0.02)
High educated	0.09** (0.03)	0.10** (0.03)	0.11*** (0.02)
Age 25-29 (Age 20-24=ref.)	0.02*** (0.00)	0.02*** (0.00)	0.02*** (0.00)
Migration background (Native=ref.)	-0.02 (0.02)	-0.02 (0.02)	-0.04* (0.02)
Maternity leave (Weeks)		-0.04** (0.01)	-0.04 (0.02)
Paid parental leave (Months)		0.01 (0.02)	-0.02 (0.04)
Unemployment rate (2010)			0.01 (0.02)
GDP			-0.03 (0.04)
Seats women in parliament			-0.02 (0.03)
Seats religious in parliament			0.08 (0.05)
Constant	-0.25*** (0.05)	-0.21** (0.06)	-0.16* (0.07)
$\tilde{R}$ -squared	0.03	0.04	0.05
N young mothers	13,644	13,644	13,644
N country	22	22	22
<i>Oster Method:</i>			
$\tilde{\beta}$ when $\delta = 0$	-0.05	-0.05	-0.09
$\tilde{\beta}$ when $\delta = 1$ and R_{max} is 1.3	-0.05	-0.05	-0.13
$\tilde{\beta}$ when $\delta = 1$ and R_{max} is 2.0	-0.06	-0.06	-0.31
$\tilde{\beta}$ when $\delta = 1$ and R_{max} is 3.0	-0.07	-0.09	-0.64

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.4 - Parameter estimates for the relationship between use of ECEC and subsequent NEET risks, including Oster bounds

	M1	M2	M3	M4
Use of ECEC (No=ref.)	-0.23*** (0.03)	-0.22*** (0.03)	-0.22*** (0.03)	-0.22*** (0.03)
Education level (Low=ref.)				
Medium educated	-0.20*** (0.02)	-0.21*** (0.02)	-0.20*** (0.02)	-0.21*** (0.02)
High educated	-0.32*** (0.03)	-0.33*** (0.03)	-0.33*** (0.03)	-0.33*** (0.03)
Age 25-29 (Age 20-24=ref.)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
Migration background (Native=ref.)	0.13** (0.04)	0.13** (0.04)	0.12*** (0.03)	0.12*** (0.03)
Net childcare costs - single hh		0.03 (0.02)	0.02 (0.02)	0.01 (0.03)
Maternity leave (Weeks)			-0.01 (0.02)	-0.01 (0.02)
Paid parental leave (Months)			-0.03 (0.03)	-0.04 (0.04)
Unemployment rate (2010)				-0.01 (0.01)
GDP				-0.02 (0.02)
Seats women in parliament				-0.01 (0.03)
Seats religious in parliament				0.02 (0.03)
Constant	1.03*** (0.10)	1.03*** (0.10)	1.04*** (0.09)	1.06*** (0.09)
$\tilde{R}$ -squared	0.13	0.13	0.13	0.14
N young mothers	13,644	13,644	13,644	13,644
N country	22	22	22	22
<i>Oster Method:</i>				
$\tilde{\beta}$ when $\delta = 0$	-0.23	-0.22	-0.22	-0.22
$\tilde{\beta}$ when $\delta = 1$ and R_{max} is 1.3	-0.21	-0.20	-0.20	-0.21
$\tilde{\beta}$ when $\delta = 1$ and R_{max} is 2.0	-0.18	-0.16	-0.16	-0.16
$\tilde{\beta}$ when $\delta = 1$ and R_{max} is 3.0	-0.13	-0.10	-0.09	-0.09

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.5.4 Alternative tests

As sensitivity tests, reported in Appendix A, we include a missing dummy for the countries with missing country-level information (Tables B2-B4), and we include young mothers aged 15-19 (Tables B5-B7). For all these alternative tests, our substantive conclusions remain the same. Lastly, we re-estimate the analyses by leaving out one single country at a time, to assess the impact of influential country cases (results are available upon request). This does not change our main conclusions.

3.6 CONCLUSIONS & DISCUSSION

This chapter explores family policy determinants of young mothers becoming NEET. We used data from the EU-LFS, containing 13,737 young mothers aged 20-29 from 22 European Union countries with a child below age 7. Our results suggests that higher costs of childcare are associated with a higher likelihood that young mothers become NEET. However, the estimate is not very precise, and becomes insignificant after including controls. This may be logical: in countries where maternity leave and parental leave cover longer periods of time, women's dependency on ECEC is less strong, and their costs may matter less. However, this may also have a statistical reason: the relatively low number of countries and the relatively high number of country level control variables make for a very conservative test of hypotheses.

To better understand how ECEC costs may affect NEET risks of young mothers, we disentangled the process of mothers becoming NEET – in relationship to family policies – and analysed the process through which young mothers become NEET in two stages. First, we analysed whether childcare costs were related to the use ECEC among young mothers. We observed that in countries in which the childcare costs were more affordable, young mothers were more likely to actually use ECEC. Second, we explored the relationship between the use of ECEC and subsequent NEET risks. We found that young mothers who used ECEC were less likely to become NEET compared to young mothers who did not use ECEC. This suggests that ECEC participation strengthens links to the labour market or education and lowers young mothers' subsequent NEET risks.

We tested the robustness of our results by including several important controls, using the bound method that is proposed by Oster (2019), and for various specifications of the model, and found that there is little concern that omitted variables will attenuate our results.

Our analyses offer meaningful and theoretically relevant explanations of the extent to which the use ECEC is associated with subsequent NEET risks. Future research can improve on these findings by using more elaborate data. For example, the EU-LFS only includes one specific ad hoc module from 2010. In 2005, the LFS also collected data on the reconciliation on family and work, but these two ad hoc modules were

not comparable. Because of this limitation, we could only analyse the data of 2010, while a comparison with 2005, or a panel survey, would have provided more in-depth information about the use of ECEC in relationship to the timing of becoming NEET (even before childbirth, immediately after childbirth or years later).

Another caveat relates to the number of countries in our dataset and the lack of data for the Nordic countries. We performed a number of sensitivity analyses to assess potential biases, but our estimates should still be interpreted with some caution and additional studies that would perform analyses with more countries or country-year combinations would be helpful. Especially the lack of the Nordic countries could result in an underestimation of the effect size because childcare costs are relatively low in the Nordics and the percentage of NEETs among young mothers is also relatively low.

Our research shows that young mothers have higher subsequent NEET risks than comparable women who do not have children. By focusing only on young mothers, we could test to what extent the costs and use of ECEC were especially important for them. The results demonstrate that actually using ECEC protects young mothers against the risk of becoming NEET. Also, lowering the cost of childcare increases the likelihood of young mothers to use ECEC.

We have been able to demonstrate a novel set of individual and institutional determinants of NEET. As such, our analyses offer relevant outcomes for future policy. Policies regarding NEETs are mostly policies targeted at young individuals and focused on their (re-)engagement in the labour market or education. This study indicates that policy makers should focus on the different needs and characteristics among them, and consider gender, motherhood and family policies as an integral part of preventing NEET risks.

3.7 REFERENCES

- Becker, G. S. (1965). A theory of the allocation of time. *The Economic Journal*, 75(299), 493-517.
- Becker, G. S. (1981). *A treatise on the family*. Cambridge, MA: Harvard University Press.
- Bonoli, G., & Reber, F. (2010). The political economy of childcare in OECD countries: Explaining cross-national variation in spending and coverage rates. *European Journal of Political Research*, 49(1), 97-118.
- Bynner, J., & Parsons, S. (2002). Social exclusion and the transition from school to work: The case of young people not in education, employment, or training (NEET). *Journal of Vocational Behavior*, 60(2), 289-309.
- Carcillo, S., Fernández, R., Königs, S., & Minea, A. (2015). NEET youth in the aftermath of the crisis: Challenges and policies. *OECD Social, Employment and Migration Working Papers*, no. 164.
- Eurofound. (2012). *NEETs - Young people not in employment, education or training: Characteristics, costs and policy responses in Europe*. Luxembourg: Publications Office of the European Union.
- Eurofound. (2013). *Caring for children and dependants: Effect on careers of young workers. Background paper*. Dublin: Eurofound.
- Eurofound. (2016). *Exploring the diversity of NEETs*. Luxembourg: Publications Office of the European Union.
- European Commission. (2010). *Proposal for a Council Decision on guidelines for the employment policies of the Member States – Part II of the Europe 2020 Integrated Guidelines*. Brussels: European Commission.
- Eurostat. (2022). Mean age of women at childbirth and at birth of first child (online data code: TPS00017). Retrieved 06 January 2023, from <https://ec.europa.eu/eurostat/databrowser/view/tps00017/default/table?lang=en>
- Gambaro, L., Stewart, K., & Waldfogel, J. (2015). A question of quality: Do children from disadvantaged backgrounds receive lower quality early years education and care in England? *British Educational Research Journal*, 41(4), 553-574.
- Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review*, 104(4), 1091-1119.
- Levels, M., Brzinsky-Fay, C., Holmes, C., Jongbloed, J., & Taki, H. (2022). *The dynamics of marginalized youth: Not in education, employment, or training around the world*. London: Routledge.
- Multilinks. (2011). Multilinks Database on Intergenerational Policy Indicators. Retrieved 02 July 2019, from <http://multilinks-database.wzb.eu>
- Nieuwenhuis, R., Need, A., & Van der Kolk, H. (2012). Institutional and demographic explanations of women's employment in 18 OECD countries, 1975-1999. *Journal of Marriage and Family*, 74(3), 614-630.
- OECD. (2011). *Doing better for families*. Paris: OECD Publishing.
- OECD. (2018). *Education at a Glance 2018: OECD indicators*. Paris: OECD Publishing.
- OECD. (2019a). Benefits and wages: Net childcare cost for parents using childcare. Retrieved 02 July 2019, from <https://doi.org/10.1787/b0781729-en>

- OECD. (2019b). *Education at a Glance 2019*: OECD Indicators. Paris: OECD Publishing.
- OECD. (2019c). Unemployment rate (indicator). Retrieved 02 July 2019, from <https://data.oecd.org/unemp/unemployment-rate.htm>
- OECD. (2020). Youth not in employment, education or training (NEET) (indicator).
- OECD. (2022). Gross domestic product (GDP). Retrieved 06 April 2022, from <https://data.oecd.org/gdp/gross-domestic-product-gdp.htm>
- Olivetti, C., & Petrongolo, B. (2017). The economic consequences of family policies: Lessons from a century of legislation in high-income countries. *Journal of Economic Perspectives*, 31(1), 205-230.
- Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37(2), 187-204.
- Pettit, B., & Hook, J. (2005). The structure of women's employment in comparative perspective. *Social Forces*, 84(2), 779-801.
- Teorell, J., Sundström, A., Holmberg, S., Rothstein, B., Pachon, N. A., & Dalli, C. M. (2022). The quality of government standard dataset, version Jan22. from <https://www.gu.se/en/quality-government>
- Thévenon, O. (2011). Family policies in OECD countries: A comparative analysis. *Population and Development Review*, 37(1), 57-87.
- Thévenon, O., & Luci, A. (2012). Reconciling work, family and child outcomes: What implications for family support policies? *Population Research and Policy Review*, 31(6), 855-882.
- Van der Lippe, T., & Van Dijk, L. (2002). Comparative research on women's employment. *Annual Review of Sociology*, 28(1), 221-241.
- Van Lancker, W., & Ghysels, J. (2016). Explaining patterns of inequality in childcare service use across 31 developed economies: A welfare state perspective. *International Journal of Comparative Sociology*, 57(5), 310-337.
- Wooldridge, J. M. (2013). *Introductory econometrics – A modern approach (5th ed.)*. Mason, OH: South-Western Cengage Learning.
- Yerkes, M. A., & Javornik, J. (2018). Creating capabilities: Childcare policies in comparative perspective. *Journal of European social policy*, 29(4), 529-544.

4

WHICH PARENTAL RESOURCES PROTECT AGAINST EARLY SCHOOL-LEAVING?

A structural equation
modeling approach

This chapter is joint work with Rolf van der Velden and Mark Levels.

4.1 ABSTRACT

Early school leaving is one of the most important predictors for NEET in the Netherlands. In this chapter, we aim to disentangle the different mechanisms explaining the relationship between socio-economic status and early school-leaving. We focus in particular on the relative contribution of a child's (non-)cognitive skills, parent's (non-)cognitive skills, parental educational attainment, and household income to early school-leaving. We combine data from the Intergenerational Transmission of Skills [ITS] dataset with data from the Netherlands Cohort Study on Education [NCO]. Our working sample includes almost 22,000 children. Based on Structural Equation Models, we find that children's own (non-)cognitive skills contribute most to the risk of early school-leaving (65% of the explained variance), followed by parent's household income (24%) and parent's educational attainment (11%). Parents' (non-)cognitive skills play an important indirect role by affecting children's (non-)cognitive skills. This indicates that not only children's skills are essential in explaining early school-leaving, but the family context also plays a significant role, both directly and indirectly.

4.2 INTRODUCTION

Early school-leaving is a societal problem (Byrne & Smyth, 2010; European Commission, 2013; Eurydice, 2015). Early school-leavers lack the minimum skills and credentials needed to ensure a smooth school-to-work transition, a successful career, and a successful life in general. This makes them more likely to become unemployed, live in poverty, and experience health problems (European Commission, 2013; Eurydice, 2015; Levels, Brzinsky-Fay, Holmes, Jongbloed, & Taki, 2022; Rumberger, 2011). Additionally, early school-leaving is also one of the best predictors for becoming NEET (Levels, Brzinsky-Fay, Holmes, Jongbloed, & Taki, 2022).

Family background plays a pivotal role in child development and children's long-term outcomes. Previous literature shows that parental socio-economic status is strongly associated with children's risk of early school-leaving (Robinson & Meredith, 2013; Robinson, Long, & Lamb, 2012; Traag & Van der Velden, 2011). However, it remains unclear why this is the case and which underlying mechanisms are important. Is early school-leaving primarily related to the primary effects of social stratification (Boudon, 1974), i.e., the intergenerational transmission of skills between parents and children? Or are secondary effects of social stratification more dominant, i.e., differential choices given certain skills levels? And if so, is this related to parents' experience in education that provide the skills and knowledge to navigate successfully in education, or is it related to the parental financial resources that are a result of parents' education?

A deeper understanding of the underlying mechanisms is crucial for implementing successful policies to combat early school-leaving. If the intergenerational transmission of skills is the most dominant mechanism, then interventions to increase skills levels in early childhood are most effective (Van Huizen & Plantenga, 2018). However, if the second mechanism is more important, policy interventions should be targeted at the crucial decision moments in the school career, e.g., by investing in counselling or a buddy-system to support young adolescents to make the right decisions (Resnjanskij, Ruhose, Wiederhold, & Woessmann, 2021). If the third mechanism is the most dominant one, policy should be aimed at removing the financial obstacles to stay in education (Herbaut & Geven, 2020).

In this chapter, we aim to disentangle the different mechanisms underlying the relation between parental socio-economic status and early school-leaving, focussing on the following research question: *What is the relative contribution of different parental resources to children's risk of early school-leaving?* To answer this research question, we use the Intergenerational Transmission of Skills [ITS] dataset (Jacobs, Vermeulen, & Van der Velden, 2021) and high-quality register data from the Netherlands Cohort Study on Education [In Dutch abbreviated as NCO (Nationaal Cohortonderzoek Onderwijs), see Haelermans et al. (2020)]. We estimate Structural Equation Models

(SEM) to assess the relative importance of causal pathways from various parental resources to the odds to become an early school-leaver.

Our chapter contributes to the literature in several ways. First, although many studies identify potential risk factors of becoming an early school-leaver (Byrne & Smyth, 2010; European Commission, 2013; Eurydice, 2015; Rumberger, 2011; Traag, 2012), a major lacuna in the previous research lies in disentangling the different mechanisms linking parental resources to early school-leaving. The reason for this lacuna is that reliable and valid data on skills of children and their parents are often lacking. Therefore, we contribute by using data that makes it possible to link different types of parental resources to early school-leaving, including parent's own skills. By using SEMs, we are able to ascertain the relative importance of these variables for explaining early school leaving.

Second, an earlier paper using the same dataset looks at children's skills at age 12 and the first choice of track levels in secondary education (Jacobs & Van der Velden, 2021). They suggest that parent's initial cognitive skills is the most dominant mechanism underlying differential choices at age 12. However, this picture may change drastically when we look at age 18 to the decision to stay in education or to leave school early. At this point in the career, secondary effects of social stratification have become more important and these are more related to parents' knowledge and skills of the educational system or to parental differences in financial resources. We will therefore assess the relative contribution of these other parental resources in explaining early school-leaving, while controlling for the effect of parent's initial cognitive skills.

4.3 THEORY

Children make several decisions during their educational career. Some of these decisions are very similar across different education systems, such as the choice of a track in secondary education or the decision to stay in school when compulsory education ends at age 18. And in many countries, these decisions are strongly affected by the socio-economic background of the children. A helpful concept underlying these socio-economic differences, is the distinction between the so-called primary and secondary effects of stratification (Boudon, 1974). The primary effects of social stratification relate to the effect of differential performance levels between children from different social strata. The secondary effects of social stratification highlight that even with the same performance level, children from different social strata make different choices. These secondary effects of social stratification relate for example to the social costs involved in social mobility. The social costs for leaving education early are higher for children from the upper social strata than for children from the lower strata. This means that there is more social pressure (from family and peers) to stay in education. Social differences in educational decision-making may be further

aggravated by risk aversion and time discount preferences that differ between social strata (Breen, Van De Werfhorst, & Jæger, 2014).

A simple way of illustrating these different effects of stratification is shown in Figure 4.1, with the relationships between parental socio-economic status and early school-leaving mediated by child's cognitive skills indicating the primary effects of social stratification and the direct effect of parental socio-economic status on early school-leaving indicating the secondary effects.

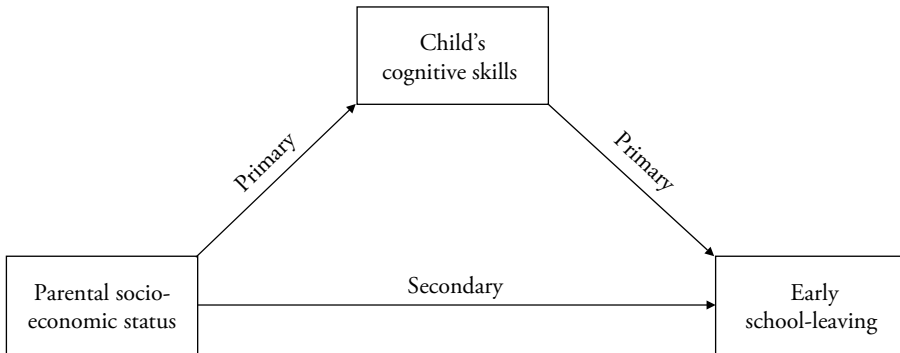
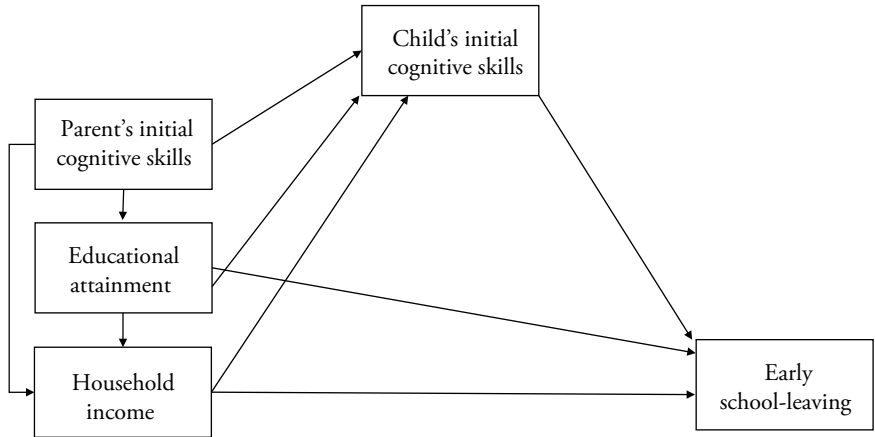


Figure 4.1 - Primary and secondary effects of social stratification and early school-leaving

Research on the effect of socioeconomic status of parents on children's educational attainment, often uses parental educational attainment and household income interchangeably. However, although both indicators are highly correlated, each reflects different mechanisms that affect children's educational attainment. Moreover, the effect of educational attainment of the parents may also relate to different mechanisms. We distinguish between three types of parental resources that affect children's educational careers. First, the educational attainment of the parents may reflect parental skills such as numeracy and literacy, key skills that are crucial for success in education. Parents can transmit these skills to their children, and as such this is an important mechanism in explaining socio-economic differences in educational outcomes. But this is not the only way parent's education may affect their children's school careers. We posit that parental educational attainment also provides them with knowledge, beliefs, expectations, and behaviours that can help them to guide their children in the educational decision-making process. Higher educated parents are more familiar with the education system, and better able to inform their children what is needed to be successful in education. The third resource we distinguish are financial resources. A high household income enables parents to provide (better) educational materials and reduces relative costs associated with staying in education (Davis-Kean, Tang, & Waters, 2019).

This means that we can extend the above model by disentangling the different types of resources related to parental socio-economic status, as shown in Figure 4.2.



Note: Based on theoretical evidence, we assume that these paths are causal relationships.

Figure 4.2 - Parental resources, children's cognitive skills and early school-leaving

In the next paragraphs we will discuss the different mechanisms depicted in Figure 4.2.

One important factor affecting early school-leaving are the child's initial cognitive skills (Cairns, Cairns, & Neckerman, 1989; Traag & Van der Velden, 2012; Traag & Van der Velden, 2011). The reason is that children with low initial cognitive skills have more difficulty in acquiring and developing further skills. This means that they have to invest more effort to stay in education (Mincer, 1974). Another reason is that because of their lower initial skills levels, they run a greater risk of failing to complete additional education programmes (cf. Fan & Wolters, 2014), which can increase their costs of staying in education. Consequently, children with low initial cognitive skills are more likely to drop out school early.

Now we turn to the paths of the parental resources: the initial cognitive skills of parents at age 12, parental educational attainment and the household income. First, previous research has already shown that there is a strong association between the cognitive skill levels of parents and their children (Anger & Heineck, 2010; Jacobs & Van der Velden, 2021; Sullivan, Moulton, & Fitzsimons, 2021). This intergenerational transmission of skills is partly related to genetic factors, and partly to environmental factors such as supporting cognitive stimulating activities (Anger & Heineck, 2010). Thus, we expect that higher parental initial cognitive skills are associated with children's

initial cognitive skills levels and therefore decrease the likelihood that their children become early school-leavers.⁹

Second, we expect an indirect relationship between parental educational attainment and early school-leaving via children's cognitive skills. Parental educational attainment, net of their own initial cognitive skills, can be seen as the parents' capacity to create a supportive learning environment in and outside the home (Pfeffer, 2008; Schütz, Ursprung, & Wößmann, 2008) which affects the development of children's cognitive skills and therefore indirectly affects early school-leaving. Accordingly, we expect that a higher educational attainment level of parents increases children's initial cognitive skills levels and therefore indirectly decreases the likelihood that their children become early school-leavers.

We also expect a direct effect of the educational attainment level of the parents on early school-leaving, net of the indirect effect via children's cognitive skills and net of the indirect effect of their own cognitive skills. We assume that in the decision-making process of early school-leaving, high-educated parents are better able to explain the importance of education to their children, help them understand how the education system works, and what the disadvantages and advantages of certain educational decisions are (Pfeffer, 2008; Schütz et al., 2008). Thus, we expect that a high educational attainment level of parents directly decreases the likelihood that their children become early school-leavers.

Third, we expect that household income is important in explaining early school-leaving. Although the Netherlands is known for its relatively low costs of education and elaborate system of financial support (Eurostat, 2020), we still expect the level of financial resources at home to affect the decision to leave school early (Farkas, 2003; Schneider, Hastings, & LaBriola, 2018). In families with more financial resources, a better learning environment can be established in the form of educational materials (such as a laptop, books, study desk) but also by providing support for extra tutoring or other out-of-school activities such as summer schools to improve school performance (Bray, 2014; De Ree, Maggioni, Paulle, Rossignoli, & Walentek, 2021; Fryer Jr & Howard-Noveck, 2020; Mori & Baker, 2010). As a result, we expect that higher financial resources will increase children's initial cognitive skill levels and therefore indirectly decrease the likelihood that they become early school-leavers.

We also expect a direct relationship between financial resources and early school-leaving. Here, the role of income may be related to the cost-benefit analyses that children and parents take into account when making the decision to leave school early. The decision is related to school-related costs (e.g. tuition fee, books etc.), to the foregone earnings while being at school rather than at work and to the expected benefits

9 Although we expect a strong indirect relationship of parent's initial cognitive skills with early school-leaving, we have no reason to assume that these parental skills will also directly affect early school-leaving of their children. This was also confirmed by an additional analysis showing that this direct path is indeed insignificant.

of further investments in schooling such as higher income and (stable) employment later in life. Since future benefits (e.g., labour market gains) are uncertain and children may weigh current and future costs and benefits differently (Breen et al., 2014), we expect that especially for children from low-income families, the costs of investing in education will outweigh benefits, which will make them more likely to leave school early. Therefore, we expect that more financial resources at home directly decrease the likelihood that children become early school-leavers.

It is not *a priori* clear which of these factors is more important in explaining early school-leaving. As indicated before, it is important to identify which mechanisms underlie the relation between socio-economic differences in early school-leaving. Is the socio-economic gradient primarily related to the role of children's initial cognitive skills (primary effects of social stratification) and if so, how do parental resources contribute to that? Or do socio-economic differences also affect the decision-making process, net of differences in cognitive skills (secondary effects of social stratification)? And if so, which parental resources are related to those differences? Before we will show this in our analyses, we will give a brief primer on the Dutch education system.

4.4 THE DUTCH EDUCATION SYSTEM

To provide context to how parental resources can affect early school-leaving in the Netherlands, we need to explain some of the structural features and peculiarities of the Dutch education system. The education system is highly stratified: at age 12 children are allocated to different tracks in secondary education. The allocation is based on the performance on a national test, made in the last year of primary education, and the primary schoolteacher's recommendation. This recommendation is based on the results of this national test, but also on the teacher's more general expectation whether a child will succeed in education. This expectation includes for example the teacher's assessment of the child's perseverance and other motivational aspects that determine success in education, or the teacher's assessment of the support of the home environment. Based on the recommendation and the test, children can enter one of six levels in secondary education. The practical training track (pro, duration four years), the lower vocational track (Vmbo-b, duration four years), the higher vocational track (Vmbo-k, duration four years), and the lower academic track (Vmbo-gt, duration four years) all prepare children for upper secondary vocational education. The medium academic track (Havo, duration five years) prepares children for universities of applied sciences. The higher academic track (Vwo, duration six years) prepares children for entry in one of the research universities. It is allowed to switch between tracks as long as the children have met the corresponding requirements. Note however, that track mobility is relatively rare, and mobility more often occurs in the form of stacking degrees in which a student obtains a diploma from the lower educational level before

starting at a higher level. After finishing secondary education, they can either leave education or enter further education (most often in a track that follows-up their previous track). Furthermore, the costs of education are relatively low and primary and secondary education is in general free to students. Post-secondary and tertiary education are not free, but the state offers financial support, which is higher for students from lower-income families (Eurostat, 2020).

In general, the Dutch education system plausibly contributes to the relative low percentage of early school-leavers in the Netherlands compared to other European countries (Eurostat, 2021). This has mainly to do with the strict requirements of obtaining a ‘starting qualification’. Between the age of 16 and 18, children are only allowed to leave school if they have acquired a ‘starting qualification’, which includes an upper secondary vocational education diploma (Mbo levels 2-4), a medium academic track diploma (Havo) or a high academic track diploma (Vwo). Young adults from age 18 onwards are no longer obliged to obtain a starting qualification or to go to school. This means that age 18 is a crucial moment to observe whether someone is an early school-leaver or not. In line with Dutch policy, we define an early school-leaver as an 18-year-old who is not in education and has not attained a starting qualification.

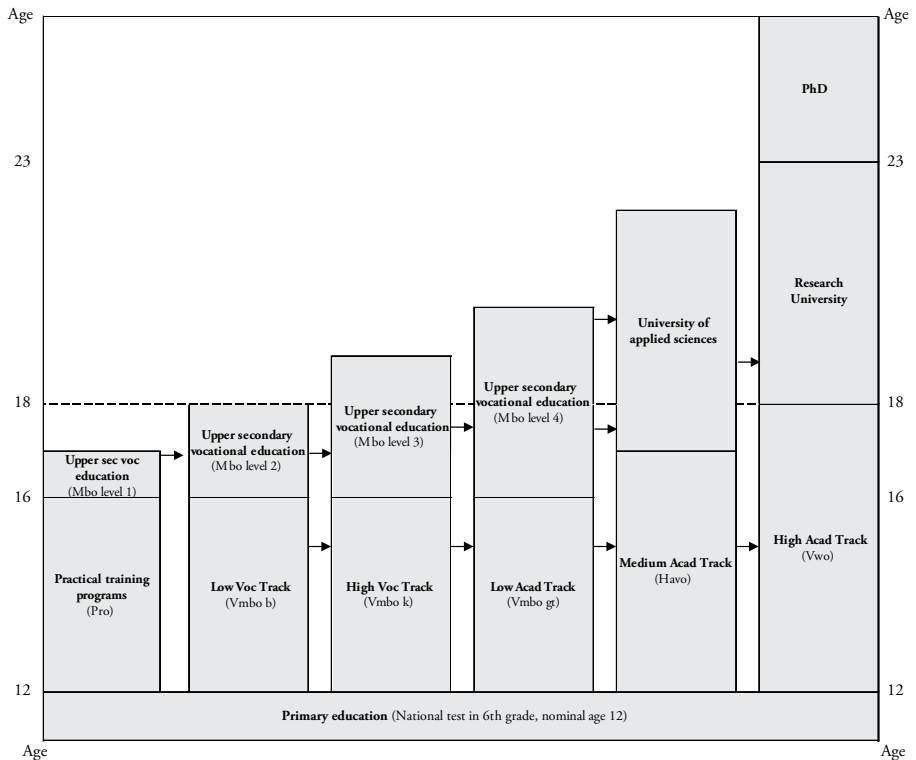


Figure 4.3 - Schematic overview of the Dutch education system

4.5 DATA, MEASUREMENTS & METHODS

4.5.1 Data

The Intergenerational Transmission of Skills [ITS] dataset includes survey data from three Dutch longitudinal panel surveys (for detailed information on the construction of the ITS dataset, see Jacobs, Vermeulen and Van der Velden (2021)). These cohort studies involve students that entered secondary education in 1977 ($N=37,280$), 1982¹⁰ ($N=16,813$) and 1989 ($N=19,524$).

At the start of the survey (at age 12), the respondents took a short version of the so-called Cito-test - at that time the only national test in the Netherlands - to assess their math and language skills. Subsequently, they were followed during their school career and their annual educational position (i.e., track and grade) was recorded until they left education. Their parents also received a questionnaire to gather information on the socio-economic background of the family.

The information of the original respondents and the information of their own children (20-40 years later) were linked. Among other variables, the children's Cito-test scores also at age 12 are included, which makes it possible to compare the initial cognitive skills of the parents with the initial cognitive skills of their children.

From the original ITS dataset, we selected only respondents that were from the two oldest cohorts, 1977 and 1982, to ensure that their children would be old enough to turn 18 in our window of observation (from year 2012 onwards). The analytical sample from the ITS dataset thus contains 20.897 parents and 35.113 of their children.

To measure early school-leaving, we complement these survey data with register data from the Netherlands Cohort Study on Education [In Dutch abbreviated as NCO (Nationaal Cohortonderzoek Onderwijs), see Haelermans et al. (2020)]. Furthermore, other register data from the Statistics Netherlands are used to measure household income.

To prepare the data for analyses, we selected children that turned 18 between 2012 and 2019. We could not use data from children that turned 18 before 2012 since children's Cito-test scores were not registered before 2006 (age 12). These selections resulted in a total sample of 22,054 children. Due to missing data on household income on age 18, our working sample exists of 21,863 children.

4.5.2 Measurements

In Table 4.1 we present the descriptive statistics of all variables. We describe how the variables are measured below.

¹⁰ The respondents from this cohort were sampled in the last year of primary education instead of the first year of secondary education.

Dependent variable

- *Early school-leaving*: Children who were not enrolled in education at age 18 and did not have a full upper secondary qualification (at least Mbo level 2, Havo or Vwo) are labelled as early school-leavers. Children that were enrolled in any kind of schooling at age 18 were not labelled as early school-leavers. As register data on secondary education is only available since 2010, children that have achieved a high school diploma before 2010 and supplemented this with a degree in upper secondary vocational education are underreported in our data (for instance children with a Vmbo-degree which is not a starting qualification, or those with an Mbo-degree). To minimize this problem, we explored in more detail their education enrolment levels after the age of 18. When we found higher levels than their starting qualification after the age of 18, we did not label them as an early school-leaver, even when they were not in school at age 18. In total, 3% of our sample exists of early school-leavers ($N=656$).¹¹
- *Variables parent*
- *Parent's initial cognitive skills*: The test score of the Cito-test at age 12 when the parent was observed in 1977 or 1982 (standardized in the original population).
- *Parent's teacher advice*: Based on the teacher's expectation of the characteristics of the child and results across the entire school career; and the results of the national test, teachers give a recommendation for the suitable secondary school track. Using the educational ladder by Bosker and Van der Velden (1989) we converted this teacher advice into years of schooling. Then the score was standardised.
- *Parent's residual of teacher advice*: As the parent's teacher advice is highly correlated with their Cito-test score, we use the residual in the teacher's advice, after controlling for the Cito-test score (standardized in the original population, see also Jacobs and Van der Velden (2021). This residual reflects a number of factors, for example the teacher's perception of parent's non-cognitive skills such as grit, perseverance and study motivation, parent's cognitive skills not measured by the test as well as teacher's perception of the educational support of the home environment needed for a successful school career. A higher score suggests a higher level on this residual (thus indicating higher levels of non-cognitive skills etc.).

¹¹ We find a rather small percentage of early school-leavers compared with the official Eurostat data (Eurostat, 2021). This is probably due to the definition of Eurostat that look at a different age group, namely those aged between 18 and 24 (Eurostat, 2021), whereas we focus on school-leavers at the age of 18 only. Therefore, students who are still trying to obtain their starting qualification after the age of 18 but do not succeed before age 24, are considered in our data as being in education, while in the Eurostat definition they are seen as early school-leaver. Put differently, we might also say that our group consists of the hard-core early school-leaver: those who already left education at age 18.

- *Parent's educational attainment*: Using the educational ladder by Bosker and Van der Velden (1989) we converted the highest obtained educational track of the parent into years of schooling and standardised this scale. A higher score on the scale means more years of schooling.
- *Household income*: the average ranking of the household in a national percentile ranking during the time the child was aged 18. This average ranking is standardized in our sample.
- *Mother*: A dummy signifying whether the surveyed parent is a mother (female) or father (male).

Variables child

- *Child's initial cognitive skills*: The test score of the Cito-test at age 12 (standardized in the original population).
- *Child's teacher advice*: Based on the teacher's expectation of the characteristics of the child and results across the entire school career; and the results of the national test, teachers give a recommendation for the suitable secondary school track. The advice was first converted into years of schooling and then standardised.
- *Child's residual of teacher advice*: Like in the case of the parents, we gain calculate the residual of the teacher's advice, after controlling for the Cito-test score of the child (standardized in the original population). A higher score suggests a higher level of this residual.
- *Daughter*: A dummy signifying whether the child is a daughter of the surveyed parent (female) or son (male).

Table 4.1 - Descriptive statistics

	<i>N</i>	Mean	SD.	Min.	Max.
<i>Dependent variable</i>					
Early school-leaving (No=ref.)	21.863	0.027		0.000	1.000
<i>Variables parent</i>					
Parent's initial cognitive skills	21.863	0.156	0.857	-2.514	2.225
Parent's educational attainment	21.863	0.192	0.959	-1.880	1.949
Household income	21.863	0.000	1.000	-3.648	1.038
Parent's residual of teacher advice	21.320	0.014	0.998	-3.742	3.968
Parent's teacher advice	21.320	0.000	1.000	-2.361	1.694
Mother (Father=ref.)	21.863	0.535		0.000	1.000
<i>Variables child</i>					
Child's initial cognitive skills	21.863	0.099	0.857	-3.621	1.788
Child's residual of teacher advice	18.197	0.053	0.946	-6.382	5.271
Child's teacher advice	18.183	0.002	0.999	-2.367	1.234
Daughter (Son=ref.)	21.863	0.505		0.000	1.000

Table 4.1 presents the descriptive statistics. We note that the mean of the standardized variables parent's initial skills, parent's educational attainment and children's initial skills is above zero. This is because the standardization is done on the original data sets. Because of the restrictions in our observation window, we observe slightly older parents, as the children of younger parents have not reached the age of 18 yet. As high-educated parents tend to get children at an older age, the sample is slightly biased towards more highly skilled parents and children.

4.5.3 Methods

To test the contribution of the parental resources (parent's initial (non-)cognitive skills, educational attainment and household income), children's own (non-)cognitive skills to children's early school-leaving, we use Structural Equation Modeling (SEM). Via SEM we attempt to model causal relations among the set of predictors that are assumed to be related to early school-leaving, as well as to provide overall indications of model-data fit. Since we have both parents' and children's mathematics and languages skills, the initial cognitive skills are based on a latent construct in which we included their math and language skills. We constrain the math skills to a fixed value of 1 to provide a scale for the respective latent variable.

To examine whether the models fit the data properly, common goodness of fit statistics are performed by looking at the Tucker–Lewis index (TLI) and the comparative fit index (CFI), which should be above .95 to indicate a good fit; the standardized root mean square residual (SRMR), which should be below .08 (Bentler, 1990); and the Root Mean Square Error of the Approximation (RMSEA), which needs to be below .05 (Steiger, 1990). For the presented path models, the goodness of fit indices show that the models fit the data well (See Appendix C, Table C1 and Table C2).

In the path diagram, we indicate latent variables by ellipses and manifest variables by boxes. The error variance for each manifest variable and disturbance on the latent variables are included in the model but not shown in the figures.

4.6 RESULTS

Using the SEM approach, we estimated the direct, indirect and total effects of the parental resources on early school-leaving. Figure 4.3 shows the results of the SEM analysis. We report the standardized path coefficients to make the estimates comparable.

Before we discuss the effects on early school-leaving, let us first have a look at the effect of parental resources on children's initial cognitive skills at age 12. We find that parent's initial cognitive skills have a strong effect on children's initial cognitive skills (0.353), while the effect of parent's educational attainment levels is about one fourth of

that size (0.112) and the effect of parents' household income still lower (0.043). When we look at the relative contribution of each of these resources, these amount to 70%, 22% and 8% respectively.¹²

Next, we continue with the relationship between children's initial cognitive skills and early school-leaving. We find that children's initial cognitive skills are negatively associated with the likelihood to become an early school-leaver (-0.118). This means that one standard deviation increase in children's initial cognitive skills is associated with an 11.8% decrease in the chance to become an early school-leaver.

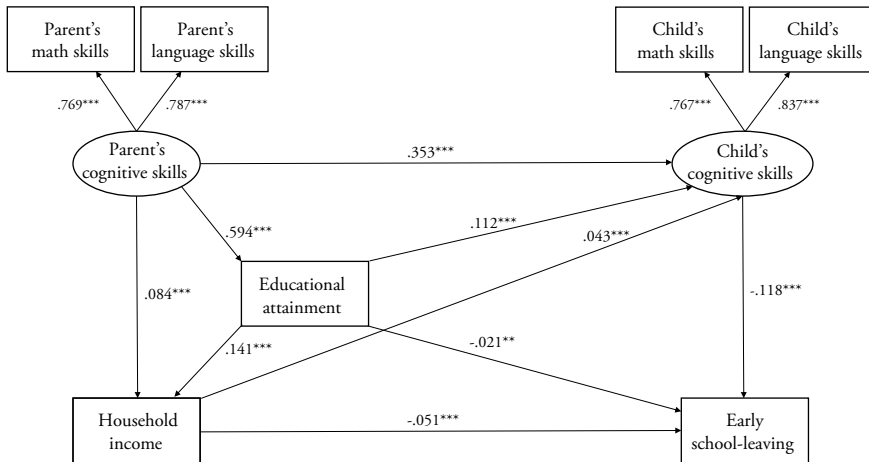
Now we turn to the direct role of the parental resources on early school-leaving. Regarding the parental educational attainment, we find that having higher educated parents decreases the likelihood that children leave school early with -0.021. This is in line with what we expected. The coefficient reflects the effect of further skills development of the parents in education, not only in terms of cognitive development but also in terms of knowing what is important to be successful and knowing how to navigate in education. For household income, we find a negative coefficient as well (-0.051) and this means that a higher household income decreases the likelihood that children become early school-leavers at age 18. This coefficient reflects the effect of financial resources on the cost-benefit analyses that adolescents and their parents make when deciding to continue in education or not. More financial resources decrease the costs of staying in education.

When we compare the standardized coefficients of the direct effects of the three parental resources with the direct effect of children's initial cognitive skills in the total sum of explained variance (Table 4.2, columns 1 and 2), we find that the direct effect of children's initial cognitive skills contributes 62%, the direct effect of parent's educational attainment contributes 11% and the direct effect of household income contributes 27%. These results suggest that in explaining early school-leaving household income has a considerable effect. This effect amounts to some forty percent of the effect of children's initial cognitive skills. Apart from that, parent's educational attainment (i.e., parent's further skills development and knowledge of the education system) still contributes, albeit not very strongly.

These figures may lead to an underestimation of the importance of family resources, as they also indirectly affect early school-leaving by affecting children's initial cognitive skills. If we look at the total (direct plus indirect) effect of the parental resources (Table 4.2, columns 5 and 6), we see that the contribution of the three resources to the total sum of explained variance is some 25% for parent's initial cognitive skills, 20% for household income and 15% for parent's educational attainment. This suggests that in general, from the three parental resources that we have measured, parent's

12 This is slightly different from what Jacobs and Van der Velden (2021) found (58%, 19% and 23%), which is due to the fact that our sample is slightly biased towards more highly skilled parents and children. Moreover, we measure household income at age 18 instead of age 12.

initial cognitive skills are most important while parent's educational attainment is least important in explaining early school-leaving.



Note: *** $p < 0.001$, ** $p < 0.010$, * $p < 0.050$; Standardized coefficients; for full model see Appendix C, Table C3.

Figure 4.4 - Parental resources, children's skills and early school-leaving

Table 4.2 - Parental resources, children's skills and early school-leaving (ESL)

	1. Direct effect on ESL		2. Indirect effect on ESL		3. Total effect on ESL	
		%		%		%
Parent's initial cognitive skills			-.071***	73.2	-.071***	24.7
Parent's educational attainment	-.021**	11.1	-.021***	21.6	-.042***	14.6
Household income	-.051***	26.8	-.005***	5.2	-.056***	19.5
Child's initial cognitive skills	-.118***	62.1			-.118***	41.1
Total	.190	100.0	.097	100.0	.287	100.0

Note: *** $p < 0.001$, ** $p < 0.010$, * $p < 0.050$; Standardized coefficients.

We saw earlier that the direct effect of children's initial cognitive skills is rather strong, taking up some 62% of the explained variance. However, other skills than those measured by the test might play a role as well. As explained earlier, this is measured by the residual of the teacher's advice. To measure these other skills, we include the residual in the teacher's advice for both parents and children in the model. This measures the effect of the teacher's advice, net of the results of the Cito-test. We interpret this coefficient as the effect of skills not measured by the test such as grit, perseverance, study behaviour or teacher's expectations about the home support

of parents. As a shorthand we call this non-cognitive skills. Figure 4.5 and Table 4.3 present the results.

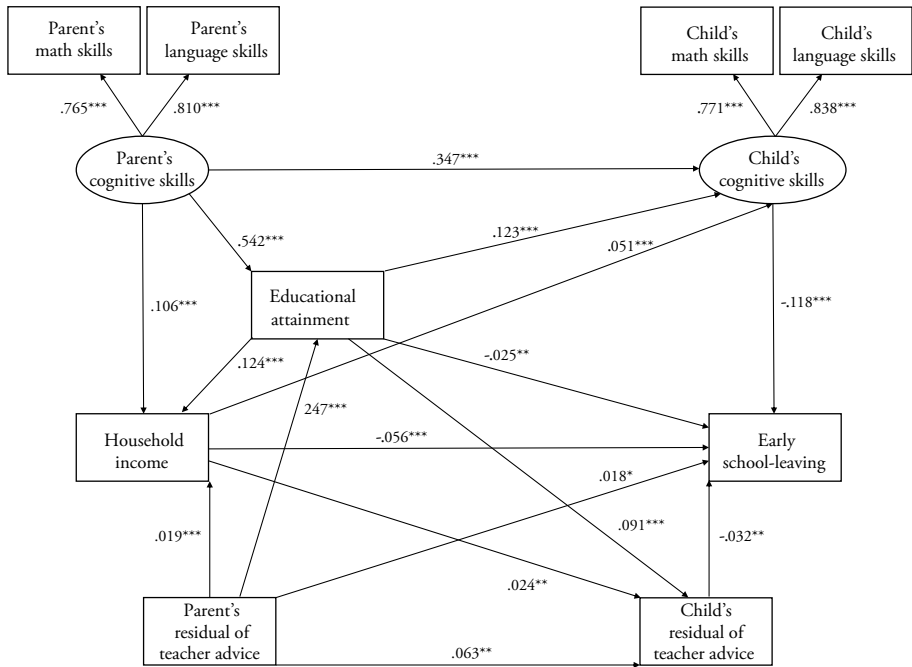


Figure 4.5 - Parental resources, children's skills and early school-leaving, including residual of teacher advice

We find that children's non-cognitive skills have an additional effect on early school-leaving of -0.032. This effect is lower than the direct effect of children's initial cognitive skills (-0.118). The relative contribution to the total sum of explained variance is 14%, while children's initial cognitive skills (51%) and parental household income (24%) have a relative higher contribution to early school-leaving. This suggests that although non-cognitive skills of children play a role in explaining early school-leaving, the role of their initial cognitive skills or the role of parental financial resources is more important. Note also that the intergenerational transmission of the non-cognitive skills from parents to children (.063) is almost six times smaller than the intergenerational transmission of initial cognitive skills (.347).

Finally, looking at the direct effects of parental resources on early school-leaving, we find that the total direct effect of parental resources (10.8%+24.2%) is almost half of the total direct effect of the cognitive and non-cognitive skills of the children (51.1%+13.9%). Again, these figures may represent an underestimation of the

importance of family resources, as they also indirectly affect early school-leaving by affecting children's initial cognitive and non-cognitive skills. If we look at the total (direct plus indirect) effect, some 58% (21.1%+14.4%+17.7%+4.5%) of the explained variance in early school-leaving is directly or indirectly related to parental resources and 'only' 42% (33.2%+9.0%) to children's cognitive and non-cognitive skills that are not affected by these family resources. This highlights the relevance of family resources in explaining early school-leaving.

Table 4.3 - Parental resources, children's skills and early school-leaving (ESL), including residual teacher advice

	1. Direct effect on ESL	%	2. Indirect effect on ESL	%	3. Total effect on ESL	%
Parent's initial cognitive skills			-.075***	61.0	-.075***	21.1
Parent's educational attainment	-.025**	10.8	-.025***	20.3	-.051***	14.4
Household income	-.056***	24.2	-.007***	5.7	-.063***	17.7
Child's initial cognitive skills	-.118***	51.1			-.118***	33.2
Parent's residual teacher advice			-.016***	13.0	-.016***	4.5
Child's residual teacher advice	-.032***	13.9			-.032***	9.0
Total	.231	100.0	.123	100.0	.355	100.0

Note: ***p<0.001, ** p<0.010, *p<0.050; Standardized coefficients.

Robustness checks

To scrutinise our result, we performed several robustness checks. First, we use a Generalized Structural Equation Model in logit (GSEM in logit) instead of the SEM model (for results see Appendix C, Table C5). No substantial differences with the original SEM model are found.

Furthermore, we create different subsamples in the data to look at potential heterogeneous effects. We look at different combinations of fathers, mothers, sons and daughters (See Appendix C, Table C6). We find that the relationship between parent's educational attainment and early school-leaving becomes less significant, however, in general, our conclusions remain the same.

4.7 CONCLUSIONS & DISCUSSIONS

This chapter aims to disentangle the mechanisms underlying the relationship between socio-economic status and early school-leaving. In particular, we focus on the relative contribution of children's (non-)cognitive skills, parent's (non-)cognitive skills, parental educational attainment, and household income to early school-leaving. We combine the Intergenerational Transmission of Skills [ITS] dataset with data from

the Netherlands Cohort Study on Education [NCO]. We use Structural Equation Models [SEM] to assess the direct, indirect, and total effects of parental resources on early school-leaving.

When we look at the direct effects, we find that the contribution of children's (non-)cognitive skills is almost 65%, household income 24%, and parent's educational attainment 11%. This underlines that children's cognitive and non-cognitive skills are very important, but that family resources are additional factors affecting early school-leaving on top of children's (non-)cognitive skills. More important, these family resources also indirectly affect early school-leaving, namely by affecting children's (non-)cognitive skills. If we take that into account, we find that the total effect of parental resources increases, with parent's initial cognitive skills having the strongest contribution (21%), followed by the household income (18%) and the parental educational attainment (14%). This implies that the family context plays a major role in explaining early school-leaving.

Although in the Netherlands the costs for education is relatively low, and subsidies or loans are available for low-income families, it is striking to see that household income contributes for almost a quarter directly to early school-leaving. On the one hand this could be related to buying better schooling equipment and to participating in shadow education, and additional tutoring to help children acquire the necessary skills to stay in school. This is represented by the indirect effect of financial resources on early school-leaving through children's initial cognitive skills. The second channel, represented by the direct effect of financial resources on early school-leaving is related to the effect on the cost-benefit analysis that children and parents make when deciding to continue in further education or to leave school early. Given the low costs of education in the Netherlands, this decision is not so much related to school-related costs (e.g. tuition fee, books etc.), but more to the foregone earnings while being in school rather than at work and to the expected benefits of further investments in schooling such as higher income and (stable) employment later in life. The cost-benefit analyses of a child from low-income families more often point to dropping out of school and starting to work, rather than investing in more education since they need the income in the short run. Apparently, the current Dutch system of subsidies or loans is not high enough for students from low-income families to balance this. Increasing the subsidies or loans for these students could possibly decrease the likelihood of early school-leaving in this group.

Furthermore, as an indicator of non-cognitive skills, we used the residual effect of the teacher's advice, net of the results of the Cito-test. We understand that this is not a perfect measure of non-cognitive skills because it includes a mix of factors such as grit, perseverance, study behaviour or teachers' expectations about the home support of parents. Still, we find a contribution of 5% of parental non-cognitive skills and 9% of children's non-cognitive skills. For the children's non-cognitive skills, this is in line

with the results of Traag and Van der Velden (2012), who looked at the direct effect of Big Five personality traits.

This chapter shows some directions for future research. First of all, more research on this topic, particularly on causality, is needed. In this chapter we focused in particular on the role of parental resources, however, other factors such as peers, and school environment could also play a role. Therefore, the path model that we presented could be extended. Second, we find that household income is an important determinant of early school-leaving, however, what would happen if a family experience a loss of their financial resources? Would this sudden income shock also affect the decision-making process of early school-leaving? Third, to get to the core effects of non-cognitive skills, future research should elaborate more on the specific personality traits of children around the time of early school-leaving, and also from their parents.

To conclude, our findings illustrate that next to children's own initial (non-) cognitive skills, parental resources play a major role in explaining early school-leaving. This indicates that the decision to leave school is not only related to children's cognitive and non-cognitive skills to be successful in education, but also to family circumstances.

4.8 REFERENCES

- Anger, S., & Heineck, G. (2010). Do smart parents raise smart children? The intergenerational transmission of cognitive abilities. *Journal of population Economics*, 23(3), 1105-1132.
- Bosker, R. J., & Van der Velden, R. K. W. (1989). Schooleffecten en rendementen. In J. Van Damme & J. Dronkers (Eds.), *Jongeren in school en beroep* (pp. 25-40). Amsterdam: Swets, Zeitlinger.
- Boudon, R. (1974). *Education, opportunity, and social inequality: Changing prospects in western society*. New York: Wiley.
- Bray, M. (2014). The impact of shadow education on student academic achievement: Why the research is inconclusive and what can be done about it. *Asia Pacific Education Review*, 15(3), 381-389.
- Breen, R., Van De Werfhorst, H. G., & Jæger, M. M. (2014). Deciding under doubt: A theory of risk aversion, time discounting preferences, and educational decision-making. *European Sociological Review*, 30(2), 258-270.
- Byrne, D., & Smyth, E. (2010). *No way back? The dynamics of early school leaving*. Dublin: The Liffey Press in association with The ESRI, NCCA and Department of Education and Science.
- Cairns, R. B., Cairns, B. D., & Neckerman, H. J. (1989). Early school dropout: Configurations and determinants. *Child development*, 60(6), 1437-1452.
- De Ree, J., Maggioni, M. A., Paille, B., Rossignoli, D., & Walentek, D. (2021). High dosage tutoring in pre-vocational secondary education: Experimental evidence from Amsterdam. *SocArxiv*.
- European Commission. (2013). *Reducing early school leaving: Key messages and policy support*. Final Report of the Thematic Working Group on Early School Leaving. Brussels: European Commission.
- Eurostat. (2020). Educational expenditure statistics. Retrieved 02 May 2022, from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Educational_expenditure_statistics#Financial_aid_to_households_and_students
- Eurostat. (2021). Early leavers from education and training by sex and labour status. Retrieved 12 October 2021, from https://ec.europa.eu/eurostat/databrowser/view/edat_lfse_14/default/table?lang=en
- Eurydice. (2015). *Tackling early leaving from education and training in Europe: strategies, policies and measures*. Eurydice and Cedefop Report. Luxembourg: Publications Office of the European Union.
- Fan, W., & Wolters, C. A. (2014). School motivation and high school dropout: The mediating role of educational expectation. *British Journal of Educational Psychology*, 84(1), 22-39.
- Farkas, G. (2003). Cognitive skills and noncognitive traits and behaviors in stratification processes. *Annual review of sociology*, 29(1), 541-562.
- Fryer Jr, R. G., & Howard-Noveck, M. (2020). High-dosage tutoring and reading achievement: Evidence from New York City. *Journal of Labor Economics*, 38(2), 421-452.
- Haelermans, C., Huijgen, T., Jacobs, M., Levels, M., Van der Velden, R., Van Vugt, L., & Van Wetten, S. (2020). Using data to advance educational research, policy and practice: Design,

- content and research potential of the Netherlands Cohort Study on Education. *European Sociological Review*, 36(4), 643-662.
- Herbaut, E., & Geven, K. (2020). What works to reduce inequalities in higher education? A systematic review of the (quasi-) experimental literature on outreach and financial aid. *Research in Social Stratification and Mobility*, 65, 1-14.
- Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: A multidisciplinary journal*, 6(1), 1-55.
- Jacobs, B., & Van der Velden, R. (2021). Exploring the uncharted waters of educational mobility: The role of key skills. *ROA Research Memorandum Series*, 006.
- Jacobs, B., Vermeulen, S., & Van der Velden, R. (2021). The Intergenerational Transmission of Skills dataset. *ROA Research Memorandum Series*, 007.
- Levels, M., Brzinsky-Fay, C., Holmes, C., Jongbloed, J., & Taki, H. (2022). *The dynamics of marginalized youth: Not in education, employment, or training around the world*. London: Routledge.
- Mincer, J. (1974). *Schooling, experience, and earnings*. New York: National Bureau of Economic Research.
- Mori, I., & Baker, D. (2010). The origin of universal shadow education: What the supplemental education phenomenon tells us about the postmodern institution of education. *Asia Pacific Education Review*, 11(1), 36-48.
- Pfeffer, F. T. (2008). Persistent inequality in educational attainment and its institutional context. *European Sociological Review*, 24(5), 543-565.
- Resnjanskij, S., Ruhose, J., Wiederhold, S., & Woessmann, L. (2021). Can mentoring alleviate family disadvantage in adolescence? A field experiment to improve labor-market prospects. *Discussion Paper*, No. 277.
- Robinson, E., & Meredith, V. (2013). Family factors in early school leaving. *Journal Of The Home Economics Institute Of Australia*, 20(2), 30-40.
- Robinson, L., Long, M., & Lamb, S. (2012). *How young people are faring*. Melbourne: The Foundation for Young Australians.
- Rumberger, R. W. (2011). *Dropping out: Why students drop out of high school and what can be done about it*. Cambridge, MA: Harvard University Press.
- Schneider, D., Hastings, O. P., & LaBriola, J. (2018). Income inequality and class divides in parental investments. *American Sociological Review*, 83(3), 475-507.
- Schütz, G., Ursprung, H. W., & Wößmann, L. (2008). Education policy and equality of opportunity. *Kyklos*, 61(2), 279-308.
- Sullivan, A., Moulton, V., & Fitzsimons, E. (2021). The intergenerational transmission of language skill. *The British Journal of Sociology*, 72(2), 207-232.
- Traag, T. (2012). *Early school leaving in the Netherlands: A multidisciplinary study of risk and protective factors explaining early school-leaving [Doctoral dissertation, Statistics Netherlands]*.
- Traag, T., & Van der Velden, R. (2012). The effects of cognitive and non-cognitive skills on early school-leaving. *METEOR Research Memorandum*(020).

- Traag, T., & Van der Velden, R. (2011). Early school-leaving in the Netherlands: The role of family resources, school composition and background characteristics in early school-leaving in lower secondary education. *Irish Educational Studies*, 30(1), 45-62.
- Van Huizen, T., & Plantenga, J. (2018). Do children benefit from universal early childhood education and care? A meta-analysis of evidence from natural experiments. *Economics of Education Review*, 66, 206-222.

5

FAMILY SHOCKS AND EARLY SCHOOL-LEAVING

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5.1 ABSTRACT

In this chapter, we further delve into the way in which family contexts explain children's early school leaving. More specifically, we explore how family shocks affect early school-leaving in the Netherlands. We look at shocks in the family that change the family dynamics, such as parental separation, large household income drops or parents becoming dependent on social welfare. We explore the effects of these shocks in conjunction. Moreover, we assess whether parent's education can moderate the effects of these shocks: are high-educated parents able to mitigate the effect of a family shock or not? And, is this related to the cognitive skills that parents have or to other effects of their educational attainment? We combine data from the Intergenerational Transmission of Skills [ITS] dataset with register data from the Netherlands Cohort Study on Education and analyse the likelihood of becoming an early school-leaver for some 22,000 children using a logistic regression design. In general, our results show that family shocks increase the likelihood of becoming an early school-leaver. We see differences in the effects according to the period in which the shocks took place. Certain shocks, like a large income drop, have an immediate and strong effect, while parents becoming dependent on social welfare or parental separation seems more indicative of a long-term process in which families are in deprived situations even before the actual shock takes place. Moreover, we find that the negative effect of an income loss shock comes from such a shock happening to mothers, while the effect of benefit dependency comes from such a shock happening to fathers.

5.2 INTRODUCTION

Early school-leavers are much more likely to become NEETs (Levels, Brzinsky-Fay, Holmes, Jongbloed, & Taki, 2022). This is partly because early school-leavers lack the minimum credentials that serve as a basis for a successful school-to-work transition and further learning and training opportunities. Moreover, early school-leavers are more likely to be unemployed, live in poverty, and experience health problems (Eurydice, 2015; Rumberger, 2011). Therefore, early school-leaving is an important societal problem (Byrne & Smyth, 2010).

In this chapter, we focus on how certain shocks in the family affect children's risk of early school-leaving. We use the term 'shocks' to indicate disruptive family events that change the family dynamics, such as a parental separation, large household income drops, or parents becoming dependent on social welfare. While we often observe such shocks as apparently sudden events, they are often manifestations of unobserved long-term processes. A parental separation for example is generally the outcome of a long-term process that may have changed the family dynamics even years before the actual separation took place.

As many of these shocks do not occur in isolation (e.g., a parental separation often implies an income shock as well), we will estimate their effects in conjunction. We will explicitly take into account when these events occur knowing that the antecedents of these shocks could have occurred earlier in time. Moreover, we will assess whether parent's education can moderate the effects of these shocks: are high-educated parents better able to dampen the effect of a family shock or not? And if so, is this related to parent's cognitive skills i.e., the information processing skills that are required in education, such as math and language skills, which parents can use to help their children in education. Or is this related to other effects of parent's education, such as their experience in education that provide the skills and knowledge to navigate successfully in education and help with educational decisions? We control for differences related to initial financial resources in the family, which are also affected by parent's education.

Our research questions are: To what extent is the risk of early school-leaving at age 18 in the Netherlands affected by family shocks in the preceding period (age 15-17)? To what extent do skills related to parents' education moderate this relationship? To answer these research questions, we use a unique combination of data, namely panel data gathered in the Intergenerational Transmission of Skills [ITS] dataset (Jacobs, Vermeulen, & Van der Velden, 2021) and high-quality register data from the Netherlands Cohort Study on Education [In Dutch abbreviated as NCO (Nationaal Cohortonderzoek Onderwijs), see Haelermans et al. (2020)] and Statistics Netherlands. We perform logistic regression analyses to investigate the relation between family shocks and early school-leaving.

Our chapter contributes to the previous literature in several ways. First, most research that explore shocks in the family in relation to early school-leaving focus on parental separation (Albertini & Dronkers, 2009; Amato, 2000; Amato & Keith, 1991; Bhrolcháin, Chappell, Diamond, & Jameson, 2000; De Leeuw, 2021; Dronkers, 1999; Dronkers, Kalmijn, & Wagner, 2006; Traag, 2012; Traag & Van der Velden, 2011). In our chapter we will look at the effect of parental separation but also other shocks that might change adolescents' decision to stay in education or not, in particular a significant income drop and parents becoming dependent on welfare benefits. These shocks reflect sudden changes in socioeconomic status. While the general relationship of early school-leaving with socio-economic status or social class is widely covered in research (De Witte, Cabus, Thyssen, Groot, & Van Den Brink, 2013; Gabay-Egozi, Shavit, & Yaish, 2010; Shavit & Blossfeld, 1993; Traag & Van der Velden, 2008), as far as we know, these particular two shocks have not been studied before in relation to early school-leaving. Moreover, they were not studied in conjunction with parental separation. Nevertheless, they can substantially affect adolescents' decisions to stay in education or leave. These shocks often occur simultaneously with parental separation and can only be understood by studying them simultaneously. For example, if one of the parents leaves the household, this will have financial consequences for the remaining parent such as a loss of income or becoming dependent on welfare benefits (Mortelmans, 2020). Similarly, the financial stress related to an income drop or welfare dependency can lead to parental separation. To get better insights into such complex and interrelated mechanisms, we study them simultaneously.

Second, previous research often compares families in which the shock took place with families where no shock took place. In our chapter, we add a comparison with families in which the shock took place after the decision to leave school early. We estimate the effect of family shocks on early school-leaving in the period immediately before turning 18 (age 15-17), with similar shocks happening later (after age 18). The latter can be regarded as an additional analysis that does not focus on the direct and immediate effect of a particular shock but rather whether such shocks may also have anticipating effects that can be observed earlier. Given the importance of the immediate effects of such shocks, we expect the effects of shocks occurring in the crucial age when decisions are made (age 15-17) to be larger than those occurring later. In that sense the comparison with the later period can serve as a placebo analysis.

Third, the use of the ITS dataset makes it possible to look at the different types of skills related to parental education. We will look at the underlying mechanism for a moderating effect of parent's education by distinguishing between the effect due to cognitive skills or other skills that have made them successful in education and will help their children to make better educational decisions.

5.3 THEORY

Through the lens of human capital theory, school-leaving can be seen as one of the educational decisions young people make during their career (Becker, 1964, 1993; Ben-Porath, 1967). Human capital theory assumes that children are rational actors that invest in schooling because they expect a return on their investment of time and energy in the form of future wages. In the classical economic version of human capital theory, children will remain in school as long as the expected benefits of attending an additional year of schooling exceed or equal the associated costs. The marginal costs include direct school-related costs (e.g., tuition fee, books), but also opportunity costs that include the foregone income while being at school rather than working. The marginal benefits include the future gains related to longer investments in schooling such as higher income and (stable) employment later in life. In this decision-making process, time discounting plays an important role: children may weigh current and future costs and benefits differently (Breen, Van De Werfhorst, & Jæger, 2014; Frederick, Loewenstein, & O'donoghue, 2002; Mischel, Shoda, & Rodriguez, 1989). People differ in the extent to which they prefer to postpone immediate consumption in return for an increase in future benefits. In educational decision-making, this is aggravated by the fact that future benefits (e.g., labour market gains) are uncertain (Breen et al., 2014).

Human capital theory explains why children stop going to school in general, but to explain early school-leaving additional assumptions are needed, e.g., about the value of certain credentials. Early school-leaving is defined as leaving school without a qualifying credential. Educational credentials are particularly relevant in the Netherlands. The Dutch education system is highly stratified (Bol & Van de Werfhorst, 2012) and typically prepares children for an occupational labour market (Iannelli & Raffe, 2007; Maurice, Sellier, & Silvestre, 1986; Smyth, Gangl, Raffe, Hannan, & McCoy, 2001). In such a system, obtaining a qualifying credential at the right level is more important than acquiring 'just' an additional year of schooling. Following the basic assumptions of human capital theory, we would assume that children become early school-leavers if the expected returns to a qualifying credential (in terms of wages or employment security) are lower than the (opportunity) costs of remaining at school.

A second issue with human capital theory is that it cannot easily explain some commonly observed regularities about early school-leaving. Notably, it cannot explain well why children from low-SES families are more likely to become early school-leavers than children from high-SES families (Gabay-Egozi et al., 2010; Shavit & Blossfeld, 1993). To explain this, a sociological adaptation of the theory posits that in addition to (opportunity) costs and future benefits, considerations about relative risk aversion also motivate educational decision-making. This version of the theory assumes that children aspire to attain a position in the social class hierarchy that is at

least as high as their parents' position (Breen & Goldthorpe, 1997; Morgan, 2005). This explains why educational decisions are related to the children's socio-economic background (Gabay-Egozi et al., 2010; Stocké, 2007). One of the reasons is related to the social costs involved in downward mobility (Boudon, 1974). Children from high-SES families will be less likely to leave school early as this will result in downward mobility and involve high social costs.

With these additional assumptions, human capital theory can explain why shocks in families can affect the likelihood that children leave school early. If families go through a change in circumstances that affect children's analyses of current (opportunity) costs, future benefits, risk aversion or time preferences, these shocks affect the risk of early school-leaving. Shocks like a parental separation, a significant income drop or parents becoming dependent on social welfare very well may. For example, when a large income drop takes place or when parents become dependent on social welfare, available financial resources will decrease, changing both the opportunity costs of not working, and decreasing the relative risk of downward mobility. In addition, a large reduction in financial resources may reduce the availability of resources needed to perform well in school, such as books and learning supplies. Moreover, it will also change the cost-benefit analyses related to the foregone earnings while being at school rather than at work and to the expected benefits of further investments in schooling such as higher income and (stable) employment later in life. Furthermore, these shocks could also affect the socio-emotional well-being (Currie, Shields, & Price, 2007; Uphold-Carrier & Utz, 2012), so that the previous intended decisions no longer seem so obvious.

We therefore expect that shocks in the family could affect the decision to stay in education and increase the risk of becoming an early school-leaver. We posit the following hypothesis:

Negative family shocks like a) a significant income drop b) becoming dependent on welfare benefits, and c) parental separation increase the likelihood that children leave school early (Hypothesis 1).

Parents may be able to influence the extent to which family shocks affect their children's school careers, ameliorating negative consequences of such negative shocks. If parents are more involved in their children's education and more strongly expecting their children to graduate, their children are less likely to leave school without a diploma (Bernardi & Triventi, 2020; Froiland, Peterson, & Davison, 2013; Rumberger, Ghatak, Poulos, Ritter, & Dornbusch, 1990; Zaff et al., 2017). Involvement, however, requires skills and knowledge. Skilled and knowledgeable parents can better provide a cognitive stimulating environment for children and help them navigate the education system (Forster & Van de Werfhorst, 2020). The question remains which skills matter, and how. Here, we distinguish two distinct types of parental resources: cognitive skills, in

particular information processing skills that are required for successful education (e.g., math and language); and parental experience with education, which help parents to explain the importance of education to their children, have them understand how the education system works, and help them make better educational decisions. We expect that these parental skills and knowledge affect early school-leaving directly, but also moderate the effects of negative family shocks. Building on their skills and knowledge, parents can reduce the negative consequences of negative shocks. We therefore expect the following:

The relation between negative family shocks and the likelihood to leave school early is weaker when parents are higher educated. This can be related a) to higher cognitive skills or b) to other effects of educational attainment, such as having more experience with the education system (Hypothesis 2).

5.4 THE DUTCH EDUCATION SYSTEM

To understand how shocks affect early school-leaving in the Netherlands it is good to have knowledge about the structure and peculiarities of the Dutch education system. The Dutch education system is highly stratified and highly standardised (Bol & Van de Werfhorst, 2012), both of which contribute to good labour market allocations. Primary education is compulsory for students from age 5 onwards and takes 8 years. Based on the results of a national test at the end of primary education (around age 12) and their primary schoolteacher's recommendation, students enter one of the six tracks in secondary education. The practical training track (pro, duration four years), the lower vocational track (Vmbo-b, duration four years), the higher vocational track (Vmbo-k, duration four years), and the lower academic track (Vmbo-gt, duration four years) all prepare students for upper secondary vocational education. The medium academic track (Havo, duration five years) prepares students for universities of applied sciences. The higher academic track (Vwo, duration six years) prepares students for entry in one of the research universities. Students are allowed to switch between tracks as long as they have met the corresponding requirements. Note however, that track mobility is relatively rare, and mobility more often occurs in the form of stacking degrees in which a student obtains a diploma from the lower educational level before starting at a higher level. After the students have finished secondary education, they can either leave education or enter further education (most often in a track that directly follows-up their previous track). Furthermore, the costs of education are relatively low and primary and secondary education is in general free to students. For the other

tracks, students are eligible for financial support, which is higher for students from low-income families (Eurostat, 2020).

Compared to other European countries, the Netherlands has a relative low percentage of early school-leavers (Eurostat, 2021). In the Netherlands, compulsory education ends at age 16, however, without a qualifying credential, the so-called starting qualification, students are still obliged to go to school until at least age 18 to obtain a qualifying diploma. Diplomas of tracks that provide a starting qualification are upper secondary vocational education (Mbo levels 2-4), the medium academic track (Havo) and the high academic track (Vwo). Students that leave education without a starting qualification are considered early school-leavers.

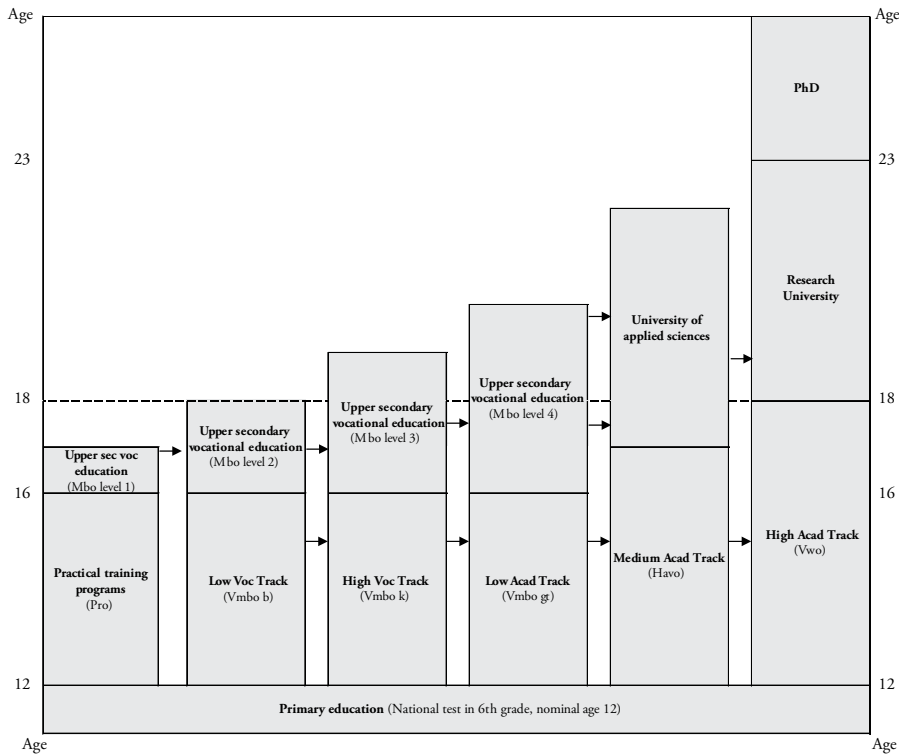


Figure 5.1 - Schematic overview of the Dutch education system

5.5 DATA, MEASUREMENTS & METHODS

5.5.1 Data

To answer our research questions, we use the Intergenerational Transmission of Skills [ITS] dataset which includes survey data from three Dutch longitudinal panel surveys,

conducted in the 70s and 80s (for detailed information on the construction of the ITS dataset, see Jacobs, Vermeulen and Van der Velden (2021)). These cohort studies involve students that entered secondary education in 1977, 1982¹³ and 1989, originally covering 37,280, 16,813 and 19,524 respondents respectively.

At the start of the survey (at age 12), the respondents took a short version of the so-called Cito-test, at that time the only national test. The Cito-test assesses math and language skills and some other domains as well. Subsequently, they were followed during their school career and their annual educational position (i.e., track and grade) was recorded until they left education. A questionnaire was sent to their parents to gather information on the socio-economic background of the family. In the ITS dataset, this was linked to information on the children of the original respondents some 20-40 years later, among others with their Cito-test scores also at age 12. From the original ITS dataset, we selected only respondents that were from the two oldest cohorts, 1977 and 1982, to ensure that their children would be old enough to turn 18 in our window of observation (from year 2006 onwards). The analytical sample from the ITS dataset thus contains 20.897 parents and 35.113 of their children.

We merge these survey data with additional high-quality register data from the Netherlands Cohort Study on Education [In Dutch abbreviated as NCO (Nationaal Cohortonderzoek Onderwijs), see Haelermans et al. (2020)] and with other register data available at Statistics Netherlands (e.g., on family shocks).

To prepare the data for analyses, we selected children that turned 18 between 2012 and 2019. We could not use data from children that turned 18 before 2012 since children's Cito-test scores were not registered before 2006 (age 12). These selections resulted in a total sample of 22,054 children. Due to missing data on household income, our working sample exists of 22,018 children.

5.5.2 Measurements

Descriptive statistics of all variables are presented in Table 5.1. We describe how the variables are measured below.

¹³ The respondents from this cohort were sampled in the last year of primary education instead of the first year of secondary education.

Dependent variable

- *Early school-leaver*: We labelled a child as an early school-leaver if the child was not enrolled in school at age 18 and did not have a full upper secondary qualification (at least Mbo level 2, Havo or Vwo). When the child was enrolled in any kind of schooling at age 18, the child was not labelled as an early school-leaver.¹⁴

The children that have achieved a high school diploma before 2010 and supplemented this with a degree in vocational education are underreported (for instance children with a Vmbo-degree which is not a starting qualification, or those with an Mbo-degree), since our data after high school starts from 2010 onwards. However, to overcome this issue we looked into their education enrolment levels after age 18 and when this was higher than the level of a starting qualification, we did not label them as an early school-leaver, even when they were not in school at age 18.

Family shocks

- *Income drop of at least 25%*: dummy that signifies whether there was a significant drop in the household income of at least 25 points in the national household percentile ranking between age 15 and age 17.
- *On benefits*: dummy whether one of the parents of the child received benefits when the child was aged 15-17, while none of the parents received benefits when the child was aged 12-14.
- *Separation*: dummy whether the parents got divorced and/or whether one of the parents moved out the household when the child was aged 15-17. The category 'unknown' includes children from which the parents were separated before the age of 15 or the children that did not live with their parents at all.

Parental resources

- *Initial cognitive skills parent*: The test score of the Cito-test at age 12 when the parent was observed in 1977 or 1982 (standardized in the original population).
- *Educational attainment parent*: The highest level of education of the parent that was observed in the ITS dataset (Low = ISCED 1, 2 or 3C short; Medium = ISCED 3 or 4; High = ISCED 5 or 6).
- *Higher education other parent*: Since in most cases only one of the parents is observed in the ITS dataset, we used register data to assess the education

¹⁴ We find a rather small percentage of early school-leavers compared to the official Eurostat data (see Appendix D, Table D1) (Eurostat, 2021). This is probably due to the definition of Eurostat that looks at a different age group, namely between age 18 and 24 (Eurostat, 2021), whereas we focus on school-leavers at the age of 18. Therefore, students who are still trying to obtain their starting qualification after the age of 18 but do not succeed before age 24, are considered in our data to be in education, while in the Eurostat definition they are seen as early school-leaver. Put differently, we might also say that our group consists of the hard-core early school-leaver: those who already left at age 18.

level of the other parent. We should note that for most of the older parents, the register data are rather incomplete, since full operation of the education register started only in 2005/2006. But the register for qualifications in higher education started earlier, in the 1980s. Therefore, we created a dummy: 'higher education' or 'other' (which also includes missing data).

- *Household income at age 12-14*: the average ranking of the household in the national percentile ranking during the time the children were aged 12-14. This average ranking is standardized in our sample. As these financial resources also affect the cost-benefit analysis that children make when deciding to continue in further education or to leave school without having a full upper secondary certificate, we will control for this in the analyses.

Furthermore, we control in our models for the *child's initial cognitive skills* on the Cito-test at age 12 (standardized in the original population), *child's gender* (male vs. female) and *child's migration background* (native vs. first and second generation migrant).

Table 5.1 - Descriptive statistics

	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>Min.</i>	<i>Max.</i>
<i>Dependent variable</i>					
Early school-leaver (No=ref.)	22,054	0.029		0.000	1.000
<i>Family shocks</i>					
Income drop of at least 25% (No=ref.)	21,825	0.035		0.000	1.000
On benefits (No=ref.)	22,054	0.797		0.000	1.000
Yes	22,054	0.149		0.000	1.000
Missing	22,054	0.054		0.000	1.000
Separation (No=ref.)	22,054	0.774		0.000	1.000
Yes	22,054	0.051		0.000	1.000
Unknown	22,054	0.176		0.000	1.000
<i>Parental resources</i>					
Initial cognitive skills parent	22,054	0.156	0.857	-2.514	2.225
Educational attainment parent (Low=ref.)	22,054	0.179		0.000	1.000
Medium	22,054	0.463		0.000	1.000
High	22,054	0.358		0.000	1.000
Higher education other parent (Other=ref.)	22,054	0.286		0.000	1.000
Household income at age 12-14	22,018	0.130	0.968	-3.531	1.408
<i>Control variables</i>					
Initial cognitive skills child	22,054	0.097	0.857	-3.621	1.788
Female (Male=ref.)	22,054	0.505		0.000	1.000
Migrant (Native=ref.)	22,054	0.059		0.000	1.000

Note: The number of observations across the three family shocks could change due to missing data and data-restrictions. See Appendix D, Tables D2-D4 for an overview of the descriptive statistics for each model separately, including the descriptive statistics for the age group 19-21.

5.5.3 Methods

Since our dependent variable on early school-leaving is dichotomous, we perform logistic regression analyses. For every type of family shock, we conduct separate analyses with early school-leaving as dependent variable. All our models control for household income at age 12-14, cognitive skills of the child, gender and migration background. Note that when we mention ‘effects’, we refer to effects in the statistical meaning (i.e., regression effects) rather than in the causal sense.

Our main analyses focus on the family shocks that happen in the critical age (between age 15 and 17) in which the children have to make a decision whether they leave or stay in education. In the second part of our research, we also look at similar shocks happening after this critical age (between age 19 and 21). This additional analysis shows whether the direct and immediate effects of the shocks in the crucial age of 15-17 are different from the possible anticipating effects of shocks happening later.

5.6 RESULTS

We start with a table describing the general effects, followed by the effect of the family shock related to a large income drop, the effect of a shock resulting from one parent becoming a benefit recipient, and the effect of shocks related to parental separation. In all analyses on family shocks, we will first describe the results on family shocks between age 15 and 17, and then compare these results to shocks that happened later (between age 19 and 21).

5.6.1 General effects

Before we add one of the family shocks to the model, we analyse the general associations between the variables and early school-leaving. Table 5.2 shows that children of higher educated parents are much less likely to leave school early (-0.230 for medium-educated parents and -0.317 for high-educated parents). The likelihood is even lower when the other parent is also higher educated (-0.419). The initial cognitive skills of parents are not significantly associated with early school-leaving. After controlling for the other resources in the family (remaining effect of education and effect of household income) and the child’s initial cognitive skills, there is no direct relation anymore with early school-leaving. Note however, that the initial cognitive skills of the parents may indirectly affect children’s outcomes through affecting their initial cognitive skills. The current analyses confirm that children’s cognitive skills are most strongly associated with early school-leaving. One standard deviation increase in the child’s initial cognitive skills (Cito-test score at age 12) decreases the likelihood of children becoming early school-leavers (-0.622). We also note that household income at age 12-14 is non-trivially associated with the early school-leaving. One standard deviation increase in the household’s overall ranking is negatively associated with the likelihood

of becoming an early school-leaver (-0.183). Furthermore, we find that women and natives are less likely to leave school early. The results of the control variables remain stable across all subsequent analyses.

Table 5.2 - Logistic regression estimates on early school-leaving

	Mo
Initial cognitive skills parent	-0.013 (0.055)
Educational attainment parent (Low=ref.)	
Medium	-0.230 ** (0.099)
High	-0.317 ** (0.132)
Higher education other parent (Other=ref.)	-0.419 *** (0.118)
Household income at age 12-14	-0.183 *** (0.040)
Initial cognitive skills child	-0.622 *** (0.045)
Female (Male=ref.)	-0.342 *** (0.082)
Migrant (Native=ref.)	0.507 *** (0.144)
Constant	-3.210 *** (0.100)
<i>N</i>	22,018

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Standard errors in parentheses.

5.6.2 Experiencing a large income drop

Table 5.3 shows the results of the analyses on the effect of a drop in the household's percentile ranking of 25 percentage points or more between age 15 and 17. Across all models we see that such an income drop is strongly related to early school-leaving (0.860 in Model 1). To illustrate the size of the effect: the likelihood is more than three times higher than the likelihood of having a medium-educated parent (-0.255 in Model 1) instead of a low-educated parent. In addition, the likelihood is over twice the size of having a higher-educated parent (-0.318 in Model 1), being female (-0.393 in Model 1) or being a migrant (0.385 in Model 1). These are very substantial statistical effects.

Table 5.3 - Logistic regression estimates on the relationship between an income drop of at least 25% and early school-leaving (age 15-17)

	M0	M1	M2	M3
Income drop of at least 25% (No=ref.)		0.860 *** (0.160)	0.819 *** (0.169)	1.234 *** (0.273)
Initial cognitive skills parent	-0.020 (0.057)	-0.014 (0.057)	0.001 (0.0587)	-0.013 (0.0570)
Income drop * Initial cognitive skills parent			-0.193 (0.189)	
Educational attainment parent (Low=ref.)				
Medium	-0.249 ** (0.103)	-0.255 ** (0.104)	-0.255 ** (0.104)	-0.198 * (0.108)
High	-0.303 ** (0.137)	-0.318 ** (0.137)	-0.317 ** (0.137)	-0.301 ** (0.142)
Income drop * Medium-educated parent				-0.772 ** (0.383)
Income drop * High-educated parent				-0.183 (0.408)
Higher education other parent (Other=ref.)	-0.395 *** (0.122)	-0.394 *** (0.122)	-0.394 *** (0.122)	-0.394 *** (0.122)
Household income at age 12-14	-0.168 *** (0.042)	-0.161 *** (0.042)	-0.162 *** (0.042)	-0.166 *** (0.042)
Initial cognitive skills child	-0.628 *** (0.047)	-0.627 *** (0.047)	-0.626 *** (0.047)	-0.627 *** (0.047)
Female (Male=ref.)	-0.390 *** (0.086)	-0.393 *** (0.086)	-0.394 *** (0.086)	-0.393 *** (0.086)
Migrant (Native=ref.)	0.389 ** (0.158)	0.385 ** (0.158)	0.388 ** (0.158)	0.384 ** (0.158)
Constant	-3.259 *** (0.099)	-3.296 *** (0.100)	-3.259 *** (0.100)	-3.329 *** (0.103)
<i>N</i>	21,820	21,820	21,820	21,820

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses.

Model 1 shows that the relationship between parent's initial cognitive skills and early school-leaving is not significant, while remaining effects of parent's education (e.g., experience with the education system and navigating skills) strongly decreases the likelihood of becoming an early school-leaver. When we look at the possible

moderating role of cognitive skills of the parents, we observe that the interaction effect is also not significant (Model 2). However, for other skills related to parent's educational attainment, we do observe a moderating effect (Model 3). We find that for children from medium-educated parents, the relationship between a large income drop and becoming an early school-leaver is weaker compared to children from low-educated parents. The effect of an income drop for children from medium-educated parents is less than half ($1.234 - 0.772 = 0.462$ in Model 3) of the effect for children from low-educated parents (1.234 in Model 3). This suggests that the residual effect of parent's education after controlling for parents' cognitive skills and financial resources (e.g., understanding why education is important and knowing how to navigate successfully in education) helps to cushion the negative effect of an income drop. However, we do not find a similar interaction effect for high-educated parents.¹⁵

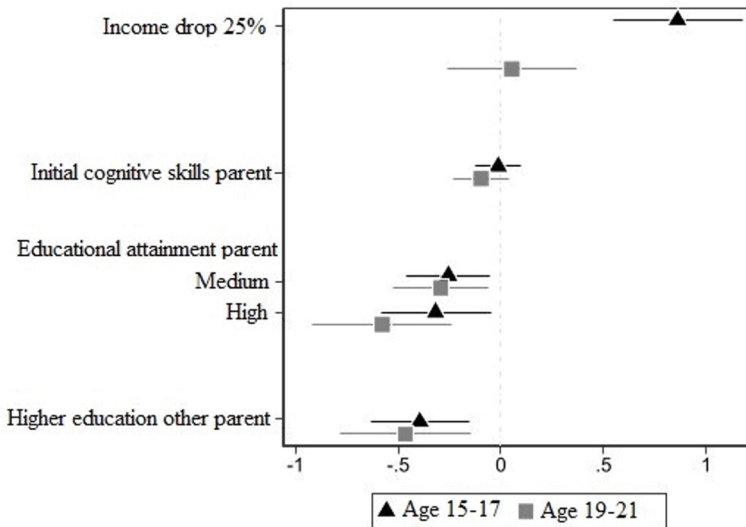


Figure 5.2 - The relationship between an income drop of at least 25% and early school-leaving, compared between age groups (age 15-17 and age 19-21) – Model 1

Figure 5.2 presents the estimates of Model 1 with only main effects for shocks happening before and after turning age 18 (for full models see Appendix D, Table D8). The strength of the estimates of our control variables does not change markedly across

¹⁵ Note that early school-leaving is very rare among high-educated parents. As a robustness check, we also looked at an income drop of 10% or more. Here we observe that the effect size of the actual income drop on the likelihood to become a school-leaver is lower, which is in line with the expectations. For the parental skills, we find similar results, except that the moderation between the income drop of at least 10% and the education level of the parent is not significant (See Appendix D, Table D6). Next, we also included year-dummies in the models: this did not change our results (See Appendix D, Table D7).

the different specifications, however, the estimate for our variable of interest does. We conclude that the effect of an income drop is only significant if it happens just before the crucial age when students have to decide whether to continue in education or not. Comparable income drops happening later at age 19-21 do not affect their chances to become an early school-leaver. This suggests that the strong effect of an income drop on early school-leaving is due to this income drop itself, rather than to unobserved factors that are associated with income drops in a family's future.

To conclude, a large drop in the family's household income substantially increases the likelihood to become an early school-leaver. There is some evidence that the experience of medium-educated parents with the education system may dampen this effect.¹⁶

5.6.3 What happens if parents become dependent on welfare benefits?

Table 5.4 shows what happens to the likelihood that children leave school early if one of their parents becomes dependent on welfare benefits. The results show that this strongly increases the likelihood of becoming an early school-leaver (0.524 in Model 1). We observe that the main effect of parental education decreases somewhat and is now significant at the 10% level only. This suggests that the likelihood of becoming dependent on social welfare is strongly correlated with parent's education, and that being on benefits weakens the protective effects of parental education. Moreover, we see no moderating effects: neither of parent's initial cognitive skills nor of their educational attainment (all interaction terms are insignificant in Models 2 and 3). In other words, there is no softening of the blow of becoming dependent on social benefits.¹⁷

¹⁶ Our conclusions remained the same after we center our data to children that turned 18 between 2013 and 2017 (See Appendix D, Table D9).

¹⁷ When we included year-dummies in our analyses, our conclusions remained the same (See Appendix D, Table D10).

Table 5.4 - Logistic regression estimates on the relationship between parents receiving benefits and early school-leaving (age 15-17)

	Mo	M1	M2	M3
On benefits (No=ref.)				
Yes		0.524 *** (0.102)	0.530 *** (0.103)	0.486 *** (0.187)
Missing		1.252 *** (0.123)	1.253 *** (0.124)	1.465 *** (0.199)
Initial cognitive skills parent	-0.0131 (0.055)	-0.0354 (0.055)	-0.0486 (0.067)	-0.0307 (0.055)
On benefits * Initial cognitive skills parent			0.041 (0.115)	
Missing * Initial cognitive skills parent			0.021 (0.143)	
Educational attainment parent (Low=ref.)				
Medium	-0.230 ** (0.099)	-0.180 * (0.100)	-0.180 * (0.100)	-0.097 (0.129)
High	-0.217 ** (0.132)	-0.230 * (0.133)	-0.228 * (0.134)	-0.271 * (0.162)
On benefits * Medium-educated parent				-0.124 (0.237)
On benefits * High-educated parent				0.403 (0.267)
Missing * Medium-educated parent				-0.342 (0.265)
Missing * High-educated parent				-0.457 (0.412)
Higher education other parent (Other=ref.)	-0.419 *** (0.118)	-0.299 ** (0.120)	-0.298 ** (0.120)	-0.316 *** (0.121)
Household income at age 12 -14	-0.183 *** (0.040)	-0.152 *** (0.0416)	-0.152 *** (0.042)	-0.152 *** (0.042)
Initial cognitive skills child	-0.622 *** (0.045)	-0.617 *** (0.045)	-0.617 *** (0.045)	-0.617 *** (0.045)
Female (Male=ref.)	-0.342 *** (0.082)	-0.361 *** (0.083)	-0.361 *** (0.082)	-0.361 *** (0.082)
Migrant (Native=ref.)	0.507 *** (0.144)	0.461 *** (0.145)	0.461 *** (0.145)	0.463 *** (0.145)
Constant	-3.210 *** (0.010)	-3.484 *** (0.102)	-3.486 *** (0.103)	-3.512 *** (0.118)
N	22,018	22,018	22,018	22,018

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses.

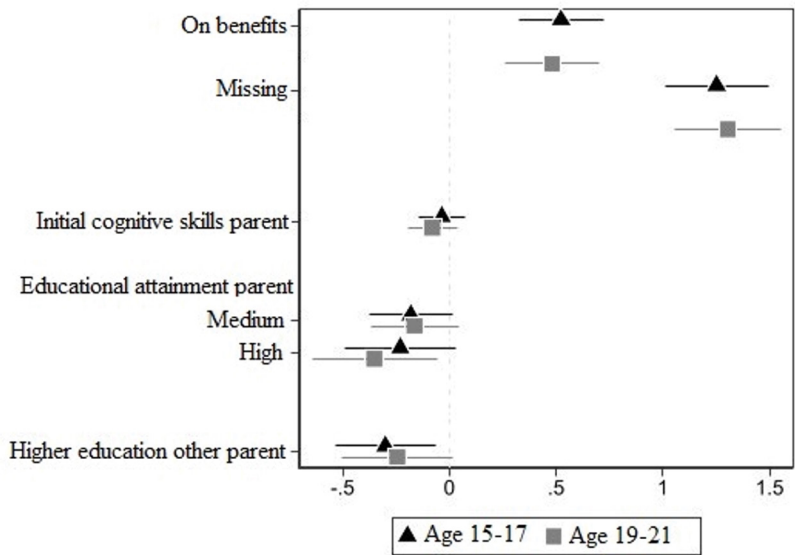


Figure 5.3 - The relationship between parents receiving benefits and early school-leaving, compared between age groups (age 15-17 and age 29-21) – Model 1

When we compare these results with similar shocks happening at later ages (age 19-21), our conclusions remain the same (Figure 5.3 for Model 1, for full models see Appendix D, Table D11). The confidence intervals of both estimates overlap substantially. This strongly suggests that the effect of the family shock resulting from one of the parents becoming dependent on benefits we observe in our analyses is not per se the immediate result of said shock. Rather, the associations we observe could be the outcome of a long-term process that may have changed the family dynamics before one the parents actually received benefits, or could be driven by unmeasured family factors that relate both to the risk of becoming welfare dependent, and to the risk of early school-leaving. The significant effect for the older ages suggests that it may also relate to the fact that families becoming welfare dependent may have been in insecure circumstances long before they start getting benefits.

To conclude, family shocks related to one of the parents becoming welfare dependent is associated with a strong increase of the likelihood of becoming an early school-leaver. However, we have no conclusive evidence that this is a direct result of the shock or that other related factors play a role.¹⁸

¹⁸ When we left out the missing category for parents receiving benefits, our conclusions remained the same (See Appendix D, Table D12). Also, our conclusions remained the same when we centered our data to children that turned 18 between 2013 and 2017, however, in this sample the relationship between cognitive skills parents and early school-leaving became sometimes significant (See Appendix D, Table D13).

5.6.4 Experiencing parental separation

The last family shock we look at is separation of the parents when the child is aged 15-17. Table 5.5 shows that a separation significantly increases the likelihood of becoming an early school-leaver (0.600 in Model 1). For the unknown category, that includes primarily children whose parents were separated before the age of 14, or children that do not live with both parents, the likelihood is even larger (0.775 in Model 1). This suggests that parental separation increases the likelihood of early school-leaving. The interaction terms between parental separation and parent's initial cognitive skills (Model 2) or parental separation and parent's educational attainment (Model 3) are not significant, suggesting that the effect of separation is not cushioned by parent's skills or education.^{19 20}

Looking at the effects of separation occurring at later ages indicates that such an event happening later (age 19-21) also significantly affects early school-leaving (Figure 5.4 for Model 1, for full models see Appendix D, Table D15). The confidence intervals overlap substantially, implying that early school-leaving is not a direct and immediate effect of parental separation. The significant effect for the older ages suggests that parental separation is the outcome of a long-term process that may have changed the family dynamics years before the actual separation took place. However, it could also be driven by unmeasured family factors that relate both to the risk of parental separation, and to the risk of early school-leaving. Furthermore, in comparison with age 15-17, for the 'unknown'-group the effect size becomes smaller. This could be related to the fact that the separation in this group took place a longer time ago (before age 14), and that after certain years the negative consequences of a separation may diminish. However, we should also take into account that the 'unknown'-group at this age, also includes children that moved out of their parents' house, e.g. for study reasons, which could also explain the smaller effect size.

In general, we find that parental separation affects the choice to continue in education or not, by increasing the risk of early school-leaving, independently of when the separation took place.²¹ In the next section, we will explore whether this effect is stable, once we control for other family shocks happening simultaneously.

19 When we included year-dummies in our analyses, our conclusions remained the same (See Appendix D, Table D14).

20 Instead of parental separation, we also looked at the possible effects when one of the parents died. However, only 0.4% in our data experienced parental death in the age 12-17, turning most results insignificant.

21 When we center our data to children that turned 18 between 2013 and 2017 our conclusions remained the same (See Appendix D, Table D16).

Table 5.5 - Logistic regression estimates on the relationship between separated parents and early school-leaving (age 15-17)

	M0	M1	M2	M3
Separation (No=ref.)				
Yes		0.600 *** (0.160)	0.605 *** (0.160)	0.726 ** (0.292)
Unknown		0.775 *** (0.101)	0.773 *** (0.101)	0.600 *** (0.173)
Initial cognitive skills parent	-0.013 (0.055)	-0.027 (0.055)	-0.037 (0.067)	-0.027 (0.055)
Separation * Initial cognitive skills parent			0.193 (0.191)	
Separation unknown * Initial cognitive skills parent			-0.0125 (0.104)	
Educational attainment parent (Low=ref.)				
Medium	-0.230 ** (0.099)	-0.242 ** (0.099)	-0.242 ** (0.099)	-0.309 ** (0.126)
High	-0.317 ** (0.132)	-0.383 *** (0.132)	-0.382 *** (0.132)	-0.459 *** (0.162)
Separation*Medium-educated parent				-0.161 (0.373)
Separation*High-educated parent				-0.206 (0.448)
Separation unknown*Medium-educated parent				0.238 (0.210)
Separation unknown*High-educated parent				0.271 (0.249)
Higher education other parent (Other=ref.)	-0.419 *** (0.118)	-0.448 *** (0.118)	-0.449 *** (0.118)	-0.447 *** (0.118)
Household income at age 12-14	-0.183 *** (0.045)	-0.033 *** (0.045)	-0.033 *** (0.045)	-0.0318 *** (0.045)
Initial cognitive skills child	-0.622 *** (0.045)	-0.615 *** (0.0450)	-0.616 *** (0.0451)	-0.614 *** (0.045)
Female (Male=ref.)	-0.342 *** (0.082)	-0.351 *** (0.082)	-0.351 *** (0.082)	-0.351 *** (0.082)
Migrant (Native=ref.)	0.507 *** (0.144)	0.443 *** (0.145)	0.441 *** (0.145)	0.447 *** (0.145)
Constant	-3.21 *** (0.096)	-3.39 *** (0.100)	-3.391 *** (0.100)	-3.339 *** (0.112)
N	22,018	22,018	22,018	22,018

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses.

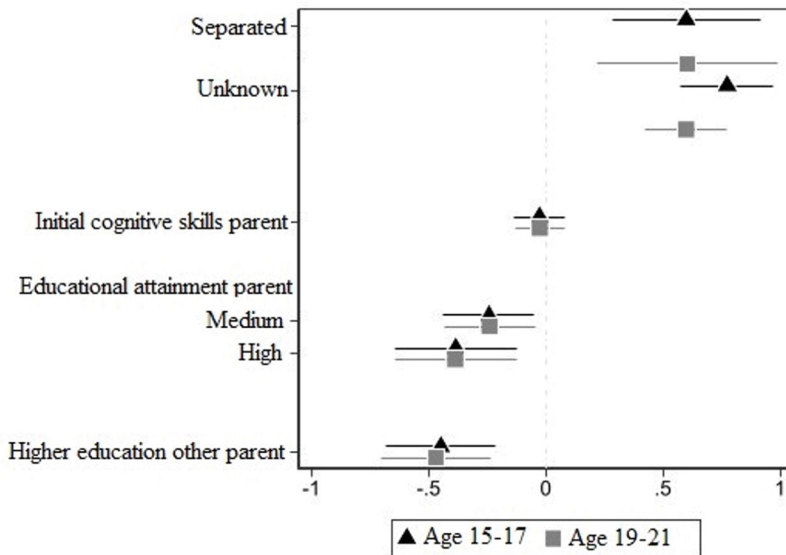


Figure 5.4 - The relationship between separated parents and early school-leaving, compared between age groups (age 15-17 and age 19-21) – Model 1

5.6.5 Are the shocks related to each other?

We have seen that a large income drop, one of the parents becoming welfare dependent and parental separation between age 15 and 17 increase the likelihood to become an early school-leaver. However, the three shocks could also be related to each other. Table 5.6, Model 1 shows that when we add the three types of shocks simultaneously in one model, both a large income drop (0.756) and receiving benefits (0.400) remain related to early school-leaving; they increase the likelihood to become an early school-leaver. However, for children who experience a separation of their parents between age 15 and 17 the relationship with early school-leaving becomes insignificant. This suggests that part of the separation effect that we found earlier can be explained by an income drop in the household or of parents becoming dependent on benefits. This suggests that it is not the separation that increases the likelihood to become an early school-leaver, but the subsequent associated income loss. We will return to this issue below.

When we compare these results with similar shocks happening at later ages (age 19-21), our conclusions are in line with what we found earlier in Figures 5.2 to 5.4. When parents become dependent on welfare benefits or separate when the child is between age 19 and 21, this seems to affect the likelihood of becoming an early school-leaver, even if we control for the income drop. This indicates that only in the case of an income drop, we find clear evidence of a direct and immediate effect (For full models see Appendix D, Table D17).

Table 5.6 - Logistic regression estimates on early school-leaving

	Mo	MI
Income drop of at least 25% (No=ref.)		0.756 *** (0.171)
On benefits (No=ref.)		
Yes		0.400 *** (0.108)
Missing		1.093 *** (0.135)
Separation (No=ref.)		
Yes		0.266 (0.177)
Unknown		0.430 *** (0.111)
Initial cognitive skills parent	-0.020 (0.057)	-0.038 (0.057)
Educational attainment parent (Low=ref.)		
Medium	-0.249 ** (0.103)	-0.216 ** (0.104)
High	-0.303 ** (0.137)	-0.283 ** (0.139)
Higher education other parent (Other=ref.)	-0.395 *** (0.122)	-0.312 ** (0.124)
Household income at age 12-14	-0.168 *** (0.042)	-0.0610 (0.048)
Initial cognitive skills child	-0.628 *** (0.047)	-0.621 *** (0.047)
Female (Male=ref.)	-0.39 *** (0.086)	-0.409 *** (0.086)
Migrant (Native=ref.)	0.389 ** (0.158)	0.321 ** (0.159)
Constant	-3.259 *** (0.100)	-3.601 *** (0.108)
<i>N</i>	21,820	21,820

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses.

Table 5.7 - Logistic regression estimates on early school-leaving (age 15-17) – controlled for other father and mother specific shocks

	Mo	Mr
Father: Income drop of at least 25% (No=ref.)		0.004 (0.223)
Mother: Income drop of at least 25% (No=ref.)		0.621 *** (0.215)
Father: On benefits (No=ref.)		
Yes		0.748 *** (0.128)
Missing		1.511 (1.111)
Mother: On benefits (No=ref.)		
Yes		0.035 (0.141)
Separation (No=ref.)		
Yes		0.402 ** (0.194)
Unknown		0.480 *** (0.123)
Initial cognitive skills parent	-0.027 (0.062)	-0.030 (0.062)
Educational attainment parent (Low=ref.)		
Medium	-0.127 (0.116)	-0.135 (0.116)
High	-0.110 (0.148)	-0.172 (0.149)
Higher education other parent (Other=ref.)	-0.323 ** (0.126)	-0.361 *** (0.127)
Household income at age 12-14	-0.248 *** (0.045)	-0.112 ** (0.0516)
Initial cognitive skills child	-0.626 *** (0.051)	-0.615 *** (0.051)
Female (Male=ref.)	-0.414 *** (0.093)	-0.44 *** (0.094)
Migrant (Native=ref.)	0.503 *** (0.164)	0.424 ** (0.166)
Constant	-3.457 *** (0.112)	-3.652 *** (0.116)
N	19,855	19,854

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses.

Since the consequences of parental separation might be different for fathers and mothers²², we re-estimated the previous model by looking whether the shock was due to an income loss or benefit dependency of the mother or the father (Table 5.7). Contrary to our findings in Table 5.6, we find that parental separation does affect early school-leaving even after controlling for the other shocks. It decreases with approximately one third (0.600 in Table 5.5 versus 0.402 in Table 5.7) due to the concurrence with an income loss for the mother or a benefit dependency of the father. This suggests that within households, it matters whom of the parents experiences an income loss or becomes dependent on welfare benefits. Apparently, an income loss of the father, or welfare dependency of the mother does not have a significant effect on early school-leaving. It remains unclear however, why this is the case.

5.7 CONCLUSIONS & DISCUSSION

In this chapter, we examine whether family shocks are related to early school-leaving, and whether parent's education can moderate this effect. Using the ITS dataset, we were able to distinguish two factors related to parent's education. First, parent's cognitive skills i.e., the information processing skills that are required in education, such as math and language, which parents can use to help their children in education. Second, other effects of parents' education such as their knowledge and experience with the education system, which helps them to explain the importance of education to their children, have them understand how the education system works, and help them make better educational decisions.

We started our analyses by looking at family shocks at age 15-17 and the likelihood to become an early school-leaver and compared these results with similar shocks happening later. We find strong evidence that in the case of a severe income drop, the shock has an immediate and direct effect on early school-leaving. Apparently, age 15-17 a critical age for children if they experience such a shock. We interpret this effect causally, as a similar income drop happening just a little later (at age 19-21) is not related to the chance to become an early school-leaver.

We also see a strong relation between a family shock resulting from parents becoming dependent on social benefits and parental separation on early school-leaving when children are at the crucial age (15-17). However, as we find comparable associations between a similar shock at a later age (age 19-21) and early school-leaving, we infer that the observed association is not necessarily driven by the shock, but involves a process that changes the family dynamics years before and after the actual shock takes place. Another explanation could be related to unmeasured family factors that are related to factors that correlate with both the welfare shock and the propensity

²² The descriptive statistics for fathers' and mothers' income drop and benefit dependency can be found in Appendix D, Table D5.

for early school-leaving, or with both the parental separation and early school-leaving. Thus, the negative effect for both age groups may suggest that receiving social benefits and parental separation is indicative of a longer period of insecure circumstances, even before the occurrence of receiving benefits. This means that the moment when parents become dependent on social benefits or when parents separate this does not have an immediate impact on young adolescents' decision to stay in school or not.

Our simultaneous analysis of the various shocks suggests that the effect of parental separation on early school-leaving is partly explained by the associated large income drop for fathers or with the chance to become welfare dependent for mothers. Controlling for other shock for fathers and mothers separately, shows that separation is still associated with an increased risk of early school-leaving. Our results suggest that a shock related to mothers experiencing an income loss or fathers experiencing a benefit dependency increase early school-leaving. That we find these differences between fathers and mothers could be related to the fact that mothers work more often part-time work in the Netherlands. This means that an income drop for mothers could be related to a reduction in the working hours. Whereas for fathers a reduction of working hour is not common, so for fathers we assume that the welfare benefit dependency is the result of unemployment.

Future research should further explore the role of financial resources in explaining early school-leaving. Our results provide strong evidence that an income drop has a direct and immediate effect on early school-leaving, even when we control for other shocks. This means that even though the Dutch education system is known for its relative low costs of education and elaborate system of financial support (Eurostat, 2020), income inequality can still affect educational careers. We think that this is not so much related to the direct costs of education (which are rather low), but to the cost-benefit analyses that children make when deciding to stay in education or leave early, including for instance the financial stress that may hamper school performance. When the financial situation is difficult, children might decide to drop out of school and start working, rather than invest in more education since they need the extra earnings on the short-term. Moreover, we also found that mother's income loss and father's welfare dependency affect early school-leaving. However, how the mechanism exactly work is still unclear. Therefore, future research should also take into account the different mechanisms of fathers and mothers regarding shocks and early school-leaving.

We also explored whether different parental resources can moderate the detrimental effects of shocks on early school-leaving and analysed the role of various resources. First, we were able to control for parental cognitive skills, using test scores of parental skills measured at age 12, which we interpret as a proxy for initial parental cognitive skills. Second, we analysed the role of parental educational attainment. Controlled for parent's initial cognitive skills and financial resources, we interpret this measure as an indication of the more intangible parental skills and resources that aid children's

journey in education, such as familiarity with the education system, institutional knowledge, and social capital. We found no evidence at all that the initial skills of parents help to soften the blow of a family shock. For the remaining effect of parent's education, we found only one moderating effect: children from medium-educated parents experience a less strongly negative effect of an income drop compared with children from low-educated parents.

To conclude, our findings illustrate that a large drop of family income, more specifically of the mother, has a strong and immediate effect on children's decision to continue in education or leave school early. We also find evidence that benefit dependency of the father and parental separation affect early school-leaving. The effects of these latter shocks however appear long before and long after the shock has taken place. Moreover, there is little evidence that parental skills can protect children for these family shocks. We suggest that future research will delve more into these associated shocks and explore under which conditions these shocks will show weaker or stronger effects, and how these different shocks are related to each other.

5.8 REFERENCES

- Albertini, M., & Dronkers, J. (2009). Effects of divorce on children's educational attainment in a Mediterranean and Catholic society: Evidence from Italy. *European societies*, 11(1), 137-159.
- Amato, P. R. (2000). The consequences of divorce for adults and children. *Journal of marriage and family*, 62(4), 1269-1287.
- Amato, P. R., & Keith, B. (1991). Parental divorce and the well-being of children: A meta-analysis. *Psychological bulletin*, 110(1), 26.
- Becker, G. S. (1964, 1993). *Human Capital: A theoretical and empirical analysis, with special reference to education* (3rd ed.). Chicago: The University of Chicago Press.
- Ben-Porath, Y. (1967). The production of human capital and the life cycle of earnings. *Journal of political economy*, 75(4, Part 1), 352-365.
- Bernardi, F., & Boertien, D. (2017). Explaining conflicting results in research on the heterogeneous effects of parental separation on children's educational attainment according to social background. *European Journal of Population*, 33(2), 243-266.
- Bernardi, F., & Triventi, M. (2020). Compensatory advantage in educational transitions: Trivial or substantial? A simulated scenario analysis. *Acta sociológica*, 63(1), 40-62.
- Bhrolcháin, M. N., Chappell, R., Diamond, I., & Jameson, C. (2000). Parental divorce and outcomes for children: Evidence and interpretation. *European Sociological Review*, 16(1), 67-91.
- Bol, T., & Van de Werfhorst, H. G. (2012). Measuring educational diversity: Tracking, vocational orientation, and standardization. *AMCIS Working Paper 1, January 2012*.
- Boudon, R. (1974). *Education, opportunity, and social inequality: Changing prospects in western society*. New York: Wiley.
- Breen, R., & Goldthorpe, J. H. (1997). Explaining educational differentials: Towards a formal rational action theory. *Rationality and society*, 9(3), 275-305.
- Breen, R., Van De Werfhorst, H. G., & Jæger, M. M. (2014). Deciding under doubt: A theory of risk aversion, time discounting preferences, and educational decision-making. *European Sociological Review*, 30(2), 258-270.
- Byrne, D., & Smyth, E. (2010). *No way back? The dynamics of early school leaving*. Dublin: The Liffey Press in association with The ESRI, NCCA and Department of Education and Science.
- Carlson, M. J., & Corcoran, M. E. (2001). Family structure and children's behavioral and cognitive outcomes. *Journal of marriage and family*, 63(3), 779-792.
- Currie, A., Shields, M. A., & Price, S. W. (2007). The child health/family income gradient: Evidence from England. *Journal of health economics*, 26(2), 213-232.
- De Leeuw, S. G. (2021). Is there a wrong time for parents to divorce? In S. G. de Leeuw (Ed.), *The intergenerational transmission of educational attainment after divorce and remarriage* [Doctoral dissertation, University of Amsterdam] (pp. 43-66). UvA-DARE.
- De Witte, K., Cabus, S., Thyssen, G., Groot, W., & Van Den Brink, H. M. (2013). A critical review of the literature on school dropout. *Educational Research Review*, 10, 13-28.
- Dronkers, J. (1999). The effects of parental conflicts and divorce on the well-being of pupils in Dutch secondary education. *European Sociological Review*, 15(2), 195-212.

- Dronkers, J., Kalmijn, M., & Wagner, M. (2006). Causes and consequences of divorce: Cross-national and cohort differences, an introduction to this special issue. *European Sociological Review*, 22(5), 479-481.
- Eurostat. (2020). Educational expenditure statistics. Retrieved 02 May 2022, from: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Educational_expenditure_statistics#Financial_aid_to_households_and_students
- Eurostat. (2021). Early leavers from education and training by sex and labour status. Retrieved 12 October 2021, from: https://ec.europa.eu/eurostat/databrowser/view/edat_lfse_14/default/table?lang=en
- Eurydice. (2015). *Tackling early leaving from education and training in Europe: Strategies, policies and measures*. Eurydice and Cedefop Report. Luxembourg: Publications Office of the European Union.
- Forster, A., & Van de Werfhorst, H. (2020). Navigating Institutions: Parents' Knowledge of the Educational System and Students' Success in Education. *European Sociological Review*, 36(1), 48-67.
- Frederick, S., Loewenstein, G., & O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of economic literature*, 40(2), 351-401.
- Froiland, J. M., Peterson, A., & Davison, M. L. (2013). The long-term effects of early parent involvement and parent expectation in the USA. *School Psychology International*, 34(1), 33-50.
- Gabay-Egozi, L., Shavit, Y., & Yaish, M. (2010). Curricular choice: A test of a rational choice model of education. *European Sociological Review*, 26(4), 447-463.
- Haelermans, C., Huijgen, T., Jacobs, M., Levels, M., Van der Velden, R., Van Vugt, L., & Van Wetten, S. (2020). Using data to advance educational research, policy and practice: Design, content and research potential of the Netherlands Cohort Study on Education. *European Sociological Review*, 36(4), 643-662.
- Iannelli, C., & Raffe, D. (2007). Vocational upper-secondary education and the transition from school. *European Sociological Review*, 23(1), 49-63.
- Jacobs, B., Vermeulen, S., & Van der Velden, R. (2021). The Intergenerational Transmission of Skills dataset. *ROA Research Memorandum Series*, 007.
- Levels, M., Brzinsky-Fay, C., Holmes, C., Jongbloed, J., & Taki, H. (2022). *The dynamics of marginalized youth: Not in education, employment, or training around the world*. London: Routledge.
- Maurice, M., Sellier, F., & Silvestre, J.-J. (1986). *The social foundations of industrial power: A comparison of France and Germany*. Cambridge, MA: MIT Press.
- Mischel, W., Shoda, Y., & Rodriguez, M. L. (1989). Delay of gratification in children. *Science*, 244(4907), 933-938.
- Morgan, S. L. (2005). *On the edge of commitment: Educational attainment and race in the United States*. Stanford University Press.
- Mortelmans, D. (2020). Economic consequences of divorce: A review. In M. Kreyenfeld & H. Trappe (Eds.), *Parental life courses after separation and divorce in Europe* (pp. 23-41). Cham, Switzerland: Springer.

- Rumberger, R. W. (2011). *Dropping out: Why students drop out of high school and what can be done about it*. Cambridge, MA: Harvard University Press.
- Rumberger, R. W., Ghatak, R., Poulos, G., Ritter, P. L., & Dornbusch, S. M. (1990). Family influences on dropout behavior in one California high school. *Sociology of education*, 63(4), 283-299.
- Shavit, Y., & Blossfeld, H.-P. (1993). *Persistent Inequality: Changing Educational Attainment in Thirteen Countries*. Social Inequality Series: ERIC.
- Smyth, E., Gangl, M., Raffè, D., Hannan, D. F., & McCoy, S. (2001). A comparative analysis of transitions from education to work in Europe (CATEWE). *Final Report, US Department of Education*.
- Stocké, V. (2007). Explaining educational decision and effects of families' social class position: An empirical test of the Breen–Goldthorpe model of educational attainment. *European Sociological Review*, 23(4), 505-519.
- Traag, T. (2012). *Early school leaving in the Netherlands: A multidisciplinary study of risk and protective factors explaining early school-leaving [Doctoral dissertation, Statistics Netherlands]*.
- Traag, T., & Van der Velden, R. (2008). Early school-leaving in the Netherlands: The role of student-, family- and school factors for early school-leaving in lower secondary education. *ROA Research Memorandum Series*, 003.
- Traag, T., & Van der Velden, R. (2011). Early school-leaving in the Netherlands: The role of family resources, school composition and background characteristics in early school-leaving in lower secondary education. *Irish Educational Studies*, 30(1), 45-62.
- Uphold-Carrier, H., & Utz, R. (2012). Parental divorce among young and adult children: A long-term quantitative analysis of mental health and family solidarity. *Journal of Divorce & Remarriage*, 53(4), 247-266.
- Zaff, J. F., Donlan, A., Gunning, A., Anderson, S. E., McDermott, E., & Sedaca, M. (2017). Factors that promote high school graduation: A review of the literature. *Educational Psychology Review*, 29(3), 447-476.

6

CONCLUSION & DISCUSSION

This dissertation focuses on vulnerable young people in society that are Not in Employment, Education or Training (NEET). The creation of this concept arose because an important group of young people were missing in the official statistics. They were not included in the education statistics, but were also not well-represented in the employment statistics, often because they were not entitled to unemployment benefits anyway. Policymakers wanted more insight into this group of young people who were not participating in the labour market nor in education, because they have higher chances of long-term socioeconomic marginalization, criminal careers, unintended pregnancies, social exclusion and severe mental and physical health problems (John Bynner & Parsons, 2002; Chen, 2011; Coles et al., 2002; OECD, 2010). Furthermore, longer periods in NEET status also make the consequences more severe (Eurofound, 2012). Additionally, these consequences do not only impact the NEETs themselves, but also their families and the society as a whole (Eurofound, 2012).

NEET rates differ strongly across countries but are also related to economic trends. For example, because of the Covid-19 pandemic, the number of NEETs in the EU (aged 15-29 years) increased from approximately 9.1 million in 2019 to 9.8 million in 2020, which is an increase in the NEET rate of 1.1% (from 12.5% to 13.6%). Therefore, the reduction of NEET rates by policy makers is key and the European Commission proposed in 2021 the European Pillar of Social Rights Action Plan. Their goal is to reduce the NEET rates to 9% by 2030 for young people aged between 15 and 29 years (European Commission, 2021).

6.1 SUMMARY OF THE FINDINGS

In this dissertation I look into possible explanations why some young people are more likely to become NEET than others. Herewith, I focus on three important groups of vulnerable young people: low literate young people, young mothers and early school-leavers. Additionally, I focus on two different perspectives. In the first two chapters, I take a macro-approach and focus on interactions between individuals and country characteristics. In the last two chapters, I take a micro and meso approach by looking at individuals and their families.

In **Chapter 2** and **Chapter 3**, the main focus is on explaining NEET rates across countries. **Chapter 2** focusses on the relationship between low-literacy and the risk to become long-term NEET. Subsequently this chapter investigates whether this relationship can be explained by country characteristics such as the vocational orientation of the educational system, the type of welfare state regime and the existence of Active Labour Market Policies (ALMPs). The ALMPs are further distinguished in enabling ALMPs that facilitate training and make it easier to combine work and family care and enforcing ALMPs that are aimed to tighten the readiness-to-work requirements and suitability criteria (Knotz, 2012). The research questions in

this chapter are: *To what extent are low levels of literacy skills associated with a high risk of being long-term NEET? How does this vary cross-nationally? To what extent can cross-national variation be explained by education and social policies?* To answer these research questions, data from the Programme for the International Assessment of Adult Competencies [PIAAC] including 25 countries and macro-level indicators on education and social policies is used. I find that low-literate young people are more likely to become long-term NEET, however, large country differences exist. In addition, I find that the institutional characteristics under consideration are related to young people's risk of becoming long-term NEET. Countries with high levels of (enabling) ALMPs appear to be more effective in keeping young people in education or training and therefore seem to be better in preventing them from long NEET periods. However, these (enabling) ALMPs seem not particularly helpful for young people with low literacy skills, but work in favour of young people with higher literacy skills. The same is true for young people living in social-democratic welfare states: they are more likely to be employed or enrolled in education/training than to be in a NEET position, but I did not find that this is specifically the case for young individuals with low literacy levels. Only enforcing ALMPs seem to affect young people with low literacy skills more than young people with higher literacy skills. However, given the overall negative effect of enforcing ALMPs this is probably not the kind of social policy a country would aim for since it increases all young people's risk to be expelled from the educational system and become NEET.

Chapter 3 focusses on young motherhood and subsequent NEET risks. The chapter explores family policy determinants of young mothers becoming NEET. Using data from the European Union Labour Force Survey [EU-LFS] including the 2010 ad-hoc module 'Reconciliation between work and family life' the following three research questions are distinguished: *To what extent do policies that determine the affordability of public childcare (national-level) affect childcare use by young mothers? To what extent does individual-level use of Early Childhood Education and Care (ECEC) reduce young mother's NEET risks?* For young mothers aged 20-29 from 22 European Union countries, I disentangle the process through which young mothers become NEET – in relationship to family policies – in two stages. First, I find that in countries in which the childcare costs are more affordable, young mothers are more likely to use ECEC. Second, I find that young mothers who use ECEC are less likely to become NEET. All in all, this chapter shows that lowering the costs of childcare increases the likelihood that young mothers use ECEC and that the actual use of ECEC helps to protect young mothers against NEET risks.

In **Chapter 4** and **Chapter 5**, I shift from a macro perspective to a micro and meso perspective where I look at individuals and their families. The prime focus is on a group that is highly at risk of being NEET or becoming NEET: early school-leavers. Both chapters focus on the role of family resources affecting early school-leaving. **Chapter 4** focusses on the mechanisms underlying the relationship between

socio-economic status and early school-leaving, in particular on the role of parental resources. The following research question is central: *What is the relative contribution of different parental resources to children's risk of early school-leaving?* To answer this research question, data from the Intergenerational Transmission of Skills [ITS] dataset and data from the Netherlands Cohort Study on Education [NCO] is used. The unique feature of this dataset is that it allows to distinguish between three types of parental resources, namely parent's initial cognitive skills, other effects of parental educational attainment, and the household income. The parent's initial cognitive skills are related to the information processing skills that are needed to be successful in education, such as math and language skills. After controlling for these initial cognitive skills, the other effects of parent's educational attainment can be understood as parent's experience in education that provide the skills and knowledge to successfully navigate in education and guide children's educational decisions. When focussing on the direct effects of children's and parental resources on early school-leaving, I find that children's (non-)cognitive skills contribute 65%, household income 24%, and other effects of parent's educational attainment 11% of the total explained variance. Together the direct effects of parental resources take up 35% of the total explained variance. Note however, that the total effect of parental resources is larger as they also affect children's (non-)cognitive skills. If I consider these indirect effects as well, the total effect of parental resources on early school-leaving is for 21% related to parent's initial cognitive skills, for 18% to the household income and for 14% to other skills related to parental educational attainment, such as their knowledge of the system and skills to successfully navigate in education. The total (direct and indirect) effects of parental resources therefore contribute up to 53% of the total explained variance.

Chapter 5 focusses on how family shocks affect early school-leaving, and to what extent parent's skills and education can moderate this relationship. The same dataset is used as in **Chapter 4** to answer the following research question: *To what extent is the risk of early school-leaving at age 18 in the Netherlands affected by family shocks in the preceding period (age 15-17)?* Family shocks are defined as disruptive family events that change the family dynamics. The three shocks observed are parental separation, a large drop in the household income, or parents becoming dependent on social welfare. I find that all three family shocks increase the likelihood of becoming an early school-leaver. However, the period in which the shocks took place is of particular importance. A large income drop has an immediate and strong effect on early school-leaving, while parental separation and parents becoming dependent on social welfare seems more indicative of a long-term process that may change the family dynamics long before and long after the actual shock takes place. Additionally, it matters which of the parents experiences the shock. Especially an income loss related to the mother, or a welfare benefit dependency related to the father, increases early school-leaving. This chapter also includes a second research question: *To what extent do skills related to parents' education moderate this relationship? In other words: Can the shock be dampened*

by having high-skilled or high-educated parents? In general, I find no such moderating effect with one exception. For the shock related to an income drop, I find that children from medium-educated parents experience a less strong negative effect than children from low-educated parents.

6.2 OVERARCHING CONCLUSIONS

Although the chapters in this dissertation cover different topics and different groups, some overarching conclusions can be drawn. First, skills play a crucial role in avoiding early school-leaving and becoming NEET. **Chapter 4** and **Chapter 5** show that lower levels of (non-)cognitive skills of children and their parents increase the likelihood of early school-leaving, directly or indirectly. **Chapter 2** indicates that low-literacy skills increase the likelihood of becoming NEET, while in **Chapter 3** I find that higher educated young mothers are less likely to become NEET than low-educated young mothers. That skills are important in multiple aspects during life is well-known (OECD, 2012). Low-skilled young people are not only more likely to become early school-leavers or NEET, but also have less chance to escape a NEET status. Young people learn most from activities in education or at work (Levels & Van der Velden, 2018), and long-term disengagement from education and work, i.e. being NEET, is likely to lead to further skills obsolescence (John Bynner & Parsons, 1998; Desjardins & Warnke, 2012; Mincer & Ofek, 1982; Salthouse, 2006). The association between skills and NEET risk is therefore likely to be exacerbated: early school-leavers and NEETs will have more difficulty in maintaining their skills or acquiring new ones. As a result, they are trapped in a vicious circle in which their skills will affect their NEET status and vice versa.

Secondly, despite the good social safety net and affordable educational system in the Netherlands, I still find that financial resources are important. **Chapter 4** shows that in general parent's financial resources contribute to a significant part to the explained variance in early school-leaving, even after controlling for other relevant resources. **Chapter 5** also describes that either a large income drop or becoming dependent on social welfare by one of the parents increases the likelihood of early school-leaving. Furthermore, **Chapter 3** shows that the costs of childcare are an important factor in explaining country differences in the actual use of ECEC and thus in the risk of young mothers to become NEET.

The importance of financial resources seem to be at least partly²³ related to the cost and benefit analyses that young people make when deciding to stay in education or leave early. For young people growing up in poverty or experiencing a large household

²³ This is not the only explanation for the observed negative relation between financial resources and early school-leaving. Financial stress may hamper school performance, and income drops may actually limit the financial resources needed to continue education.

income drop at crucial ages, the cost and benefit analyses of investing in school differs from those young people who do not experience such income-related problems. For young people who have less money to spend, receiving income from current work will be more relevant than to invest in extra education or training. Even when considering the fact that the extra investment in education or training could result in better work perspectives or higher income in the future.

The same holds for childcare costs. In fact, for young mothers who receive a relatively low income, on the short-term quitting work and becoming NEET is more attractive than spending (most of) their income on childcare. However, the long-term consequences of such a choice may be quite negative.

6.3 POLICY IMPLICATIONS

This dissertation shows that becoming an early school-leaver or NEET is systematically related to factors that are beyond the control of an individual: the resources in the family they were born into or the costs of education in their country. This also implies that there is an urgent need to implement policies that are targeted at early school-leavers and NEET. Not only for the individual themselves, but also for their families and the society as whole. The main focus of the policy implementations should be on the one hand on skills development and on the other hand on reducing costs of education and ECEC.

This dissertation shows that skills are crucial to prevent early school-leaving and to reduce NEET risks. This implies that increasing skill levels serves both goals. Current policies already focus on the development of skills at early ages. Previous research has shown that the investment in skills is important, and should be implemented as early as possible (OECD, 2018). Van Huizen and Plantenga (2018) show in their meta-analysis that ECEC programmes are effective if they are of sufficient quality. More importantly, these programmes are particularly effective for disadvantaged children. Therefore, given the gains of ECEC in the long term, policy implementations should focus more on the improvement of skill development, in particular for the ones who need it most: children from lower socio-economic background. Unfortunately, high-quality ECEC programmes are typically also more expensive. As shown in **Chapter 3**, high childcare costs increase subsequent NEET risks for mothers, therefore policies on ECEC should not only take into account the quality for child development, but also the affordability of these programmes.

In addition, this dissertation suggests that skill development policies should also focus on young adults, in particular those with low (literacy) skills as they also have a great risk of becoming NEET. As mentioned before, for young NEETs it is harder to maintain current skill levels and acquire new ones. As a result, they are trapped in a vicious circle in which their low skill levels increase their risk to become NEET,

while conversely their NEET status negatively affects their skill development. Policy makers should thus also focus on skill development at later ages. This can be done, for example, by offering learning opportunities at work as also suggested by the OECD (OECD, 2021). However, this is not enough since young people with low skills are at increased risk of not having a job at all. For these young people, (enabling) ALMPs might work since this could include job-search assistance, training programmes and subsidized employment (Maguire, Levels, Brzinsky-Fay, Jongbloed, Taki, 2022). However, these policies tend to fail to benefit the most vulnerable groups (**Chapter 3**). Moreover, although several initiatives have been taken in the past, Windisch (2016) reports that successful interventions for adults with low basic skills are still relatively rare and often the evaluation evidence is weak. It is not easy to find a good solution here. Probably, the most promising interventions are personalised programmes for NEETs with low skills because most of the times they also have other problems as well. Such a personalised programme should therefore have a more integral approach, for example by using neighbourhood coaches who do not only focus on the skill development but also on the successful integration in society. Such professional workers could help young people with their needs and use as many tools as possible to support the personal and professional development of NEETs (Youth Social Rights Network, 2016).

Furthermore, there is a multiplier effect of skills development as skills are also transferred across generations. This dissertation again demonstrates that there is an intergenerational transmission of skills from parents to their children. A better skills development for young adults, will ultimately also affect their future offspring and thus future levels of early school-leaving or NEET status. This makes it even more important for policy makers to focus on the development of skills across generations and not only on young children.

However, skills are not the only factor. I have shown how important financial resources are in preventing early school-leaving. There may be several reasons for this. For example, even in the Netherlands, the costs associated with education may be too high for low-income households (Eurostat, 2020). Furthermore, financial stress of parents may negatively impact their children's educational success and increase the risk of early school-leaving (Joo, Durband, & Grable, 2008). Finally, opportunity costs associated with not working may affect educational decision-making, particularly in low-income families. To mitigate these effects, policy makers may consider various policies. The most straightforward policy implementation is probably to increase income-related subsidies, by providing higher subsidies for pupils and students from low-income families. This would serve to lower the opportunity costs of not working associated with staying in school and reduce financial stress for children. Furthermore, providing better information about the usefulness of the extra investment in schooling by explaining the long-term benefits in terms of better labour market perspectives and higher incomes in the future could also help children (and parents) in making

better educational decisions. Earlier research has already shown that a buddy system in which a role model (e.g., an older student) makes young people aware of the long-term beneficial impact of certain choices at an early age can be very successful (Resnjanskij, Ruhose, Wiederhold, & Woessmann, 2021). In this way, they will receive personalised help, which is based on their own needs and this may substitute the negative effects of having low-skilled parents.

As this dissertation shows, parents play an important role in the educational decision making process and the above-mentioned example of a buddy system can only complement, but not substitute parents' role. Therefore interventions should also focus on increasing parental involvement, for example by organising parental meetings that explain the structure of the educational system, the curriculum, the assessment and evaluation criteria, and also teach other supportive skills for parents (Flores, Morgan, Rivera, & Clark, 2019; Manzoni & Rolfe, 2019; Montero-Sieburth & Turcatti, 2022). In this way, parents improve their understanding about the advantages of extra schooling for a better future for their children, which could help in making better educational decisions.

An important consideration for all policy interventions is that the right target group is reached. Importantly, this is not always the case as described in **Chapter 2** of this dissertation. The positive effects of AMLPs seemed mainly caused by the fact that policies are not designed for the circumstances and needs of the most vulnerable group of young people. This could be related to the urge for policy makers to decrease the overall number of NEETs in a country, which induces an incentive to focus first on the ones with the more superficial problems rather than the most vulnerable NEETs (Jongbloed & Giret, 2021). An additional problem is that those most at risk are not always aware of their need of extra help. For example, research has shown that those with low basic skills are often unable or unwilling to recognise their own lack of skills and therefore do not feel the urge to improve them (Bynner & Parsons, 2006). Therefore, for any intervention to be successful, policy makers should clearly define and target the most vulnerable group of young people. Missing this vulnerable group of young people could also raise concerns about rising inequalities (Mawn, Oliver, Akhter, Bamba, Torgerson, Bridle and Stain, 2017).

In conclusion, policy makers should focus on more personalised programmes to help preventing early school-leaving and to reduce NEET risks. Since the lack of skills or financial resources often go hand in hand with other problems, it is important to help these young people with their integration in society. A neighbourhood coach or buddy system can help to see the relation with other problems and assist in developing an integral approach in tackling this multifaceted problem.

6.4 FUTURE RESEARCH

The results reported in this dissertation primarily relied on cross-sectional and longitudinal data to explore the effects of skills, families, and country characteristics on early school-leaving and NEET risk. While this dissertation offers meaningful and theoretically relevant explanations of early school-leaving and NEET risks, future research can improve the findings by using better data.

Regarding the country characteristics higher-quality macro-data is necessary. The macro-data used in this dissertation is not available for all covered countries. The lack of data could result in possible selection biases. Moreover, not all macro-data is available for all covered years. It can be assumed that for most countries that were studied, the used macro-data have not significantly changed over the past few years, and the ranking of the countries has not or only barely changed. To overcome these issues in the future, follow-up research should invest in collecting better and time-varying macro-data. For example, macro-data on the education systems and social policies across countries.

At the individual level, early school-leaving and NEET risks is not only affected by the family, but also by peers, the neighbourhood and the school environment (Traag & Van der Velden, 2011). Therefore, the research described in this dissertation should be extended in the future by taking into account more external factors that could explain the underlying mechanisms on early school-leaving, but also on the risk to become NEET.

The development of a good measure of NEETs is difficult with the available data. In the data used in **Chapter 4** and **Chapter 5** information on possible training or unpaid work was missing, which made it hard to construct a NEET indicator. Historical data on NEET prevalence was not available in the data used in **Chapter 2** and **Chapter 3** whereas it was unknown if the young people were NEET before. Moreover, it was also not possible to assess the duration of NEET status. Previous research has already shown the importance of a more dynamic approach of NEET (Brzinsky-Fay, 2007; Contini, Filandri, & Pacelli, 2019; Levels, Brzinsky-Fay, Holmes, Jongbloed, & Taki, 2022), and therefore it would be interesting to see whether my results would hold when taking into account a more dynamic measure of NEET.

An important issue is that it was not possible to draw strong causal inferences. This should preferably be done using a causal design to understand the connection between the causes and consequences. Future research should therefore exploit the possibility of using different research designs, such as difference-in-difference designs, randomized control trials (RCTs) or natural experiments.

Finally, future research should focus more on the evaluation of the effectiveness of policies aimed at combatting NEET. For example, RCTs could be carried out to evaluate the causal effects of a new policy implementation before an approach is widely implemented. In this RCT, young people could be randomly assigned to

a control group (not being affected by the new policy) or a treatment group (being affected by the new policy) and see to what extent the vulnerable NEETs are able to reintegrate in education or the labour market. In this way, the RCT can be used as a measure whether the pilot is effective or not.

Lastly, this dissertation brought up new research questions. First, **Chapter 4** focusses on the relative contribution of parents towards early school-leaving in the Netherlands. Do these findings hold for other countries as well? And do they also affect NEET status? **Chapter 5** focusses on family shocks and early school-leaving. A more in-depth focus on, for example, the timing of shocks and the differences in the contribution of parental resources between fathers and mothers would be appropriate in the future. The focus of **Chapter 2** is on low literacy skills, however, do these results remain the same when looking at low numeracy skills? And to what extent can low levels of literacy be compensated by higher levels of numeracy or vice versa? What is the effect of a cumulative disadvantage in both domains? The main focus of **Chapter 3** is on ECEC costs and NEET, however, to what extent are the NEET risks also affected by informal childcare (e.g. grandparents) or the duration of paternity leave? And are father in the same age group at the same risk of being NEET?

To conclude, this dissertation shows that the problems that vulnerable NEETs experience are difficult to solve. NEETs, especially the most vulnerable NEETs, are difficult to reach, and policies are often less targeted at the most vulnerable young people. Policies that do target them are less effective for this group. This makes long-term NEETs a wicked problem.

6.5 REFERENCES

- Brzinsky-Fay, C. (2007). Lost in transition? Labour market entry sequences of school leavers in Europe. *European sociological review*, 23(4), 409-422.
- Bynner, J., & Parsons, S. (1998). *Use It or Lose It? The Impact of Time out of Work on Literacy and Numeracy Skills*. London: ERIC.
- Bynner, J., & Parsons, S. (2002). Social exclusion and the transition from school to work: The case of young people not in education, employment, or training (NEET). *Journal of vocational behavior*, 60(2), 289-309.
- Bynner, J., & Parsons, S. (2006). *New light on literacy and numeracy: Summary report*. London: NDRC Research Report, National Research and Development Centre for Adult Literacy and Numeracy (NDRC).
- Chen, Y. W. (2011). Once a NEET always a NEET? Experiences of employment and unemployment among youth in a job training programme in Taiwan. *International Journal of Social Welfare*, 20(1), 33-42.
- Coles, B., Hutton, S., Bradshaw, J., Craig, G., Godfrey, C., & Johnson, J. (2002). *Literature review of the costs of being "not in education, employment or training" at age 16-18*. London: Department for Education and Skills, Research Report 347.
- Contini, D., Filandri, M., & Pacelli, L. (2019). Persistency in the NEET state: A longitudinal analysis. *Journal of Youth studies*, 22(7), 959-980.
- Desjardins, R., & Warnke, A. J. (2012). Ageing and skills: A review and analysis of skill gain and skill loss over the lifespan and over time. *OECD Education Working Papers*, No. 72.
- Eurofound. (2012). *NEETs - Young people not in employment, education or training: Characteristics, costs and policy responses in Europe*. Luxembourg: Publications Office of the European Union
- Eurostat. (2020). Educational expenditure statistics. Retrieved 02 May 2022, from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Educational_expenditure_statistics#Financial_aid_to_households_and_students
- Flores, R. Q., Morgan, P., Rivera, L., & Clark, C. (2019). Latinx family engagement in schools and surrounding communities: Assessing the impact of parent (and other family member) development on improving student educational outcomes at gene ward elementary school. *Education sciences*, 9(2), 149.
- Joo, S. H., Durband, D. B., & Grable, J. (2008). The academic impact of financial stress on college students. *Journal of College Student Retention: Research, Theory & Practice*, 10(3), 287-305.
- Knotz, C. M. (2012). Measuring the 'new balance of rights and responsibilities' in labor market policy: A quantitative overview of activation strategies in 20 OECD countries. *ZeS-Working Paper*, No. 06/2012.
- Levels, M., Brzinsky-Fay, C., Holmes, C., Jongbloed, J., & Taki, H. (2022). *The dynamics of marginalized youth: Not in education, employment, or training around the world*. London: Routledge.

- Levels, M., & Van der Velden, R. (2018). Use-it-or-lose-it? Explaining age-related differences in key information processing skills. In I. Kirsch, E. Gonzalez, M. Von Davier, & K. Yamamoto (Eds.), *The Importance of Skills and How to Assess Them*. Cham: Springer International Publishing AG.
- Maguire, S., Levels, M., Brzinsky-Fay, C., Jongbloed, J., & Taki, H. (2022). Policy Interventions Targeting NEETs in Different Institutional Settings. In M. Levels, C. Brzinsky-Fay, C. Holmes, J. Jongbloed, & H. Taki (Eds.), *The Dynamics of Marginalized Youth* (pp. 180-204). London: Routledge.
- Manzoni, C., & Rolfe, H. (2019). How schools are integrating new migrant pupils and their families. *National institute of economic and social research*.
- Mawn, L., Oliver, E. J., Akhter, N., Bamba, C. L., Torgerson, C., Bridle, C., & Stain, H. J. (2017). Are we failing young people not in employment, education or training (NEETs)? A systematic review and meta-analysis of re-engagement interventions. *Systematic reviews*, 6(16), 1-17.
- Mincer, J., & Ofek, H. (1982). Interrupted work careers: Depreciation and restoration of human capital. *Journal of Human Resources*, 17(1), 3-24.
- Montero-Sieburth, M., & Turcatti, D. (2022). Preventing disengagement leading to early school leaving: Pro-active practices for schools, teachers and families. *Intercultural Education*, 33(2), 139-155.
- OECD. (2010). *Off to a good start? Jobs for youth*. Paris: OECD Publishing.
- OECD. (2012). *Better skills, better jobs, better lives: A strategic approach to skills policies*. Paris: OECD Publishing.
- OECD. (2018). *Early learning matters*. Paris: OECD publishing.
- OECD. (2021). *Skills outlook 2021: Learning for life*. Paris: OECD publishing.
- Resnjanskij, S., Ruhose, J., Wiederhold, S., & Woessmann, L. (2021). Can mentoring alleviate family disadvantage in adolescence? a field experiment to improve labor-market prospects. *IZA Discussion Papers, No. 14097*.
- Salthouse, T. A. (2006). Mental exercise and mental aging: Evaluating the validity of the “use it or lose it” hypothesis. *Perspectives on Psychological Science*, 1(1), 68-87.
- Traag, T., & Van der Velden, R. (2011). Early school-leaving in the Netherlands: The role of family resources, school composition and background characteristics in early school-leaving in lower secondary education. *Irish Educational Studies*, 30(1), 45-62.
- Van Huizen, T., & Plantenga, J. (2018). Do children benefit from universal early childhood education and care? A meta-analysis of evidence from natural experiments. *Economics of Education Review*, 66, 206-222.
- Windisch, H. C. (2016). How to motivate adults with low literacy and numeracy skills to engage and persist in learning: A literature review of policy interventions. *International Review of Education*, 62(3), 279-297.
- Youth Social Rights Network. (2016). *In NEET of a coach! Report of the study session organised by the Youth Social Rights Network in co-operation with the European Youth Centre of the Council of Europe*. European Youth Centre Strasbourg: 15 – 22 May 2016

IMPACT

Objective

The main objective of this dissertation is to explain why some vulnerable young people in society are more likely to become Not in Employment, Education or Training (NEET) as compared with others. The NEETs concept is relevant for policy makers because NEETs are less well integrated in society and are at greater risk of long-term socioeconomic marginalization, criminal careers, unwanted pregnancies, social rejection, and serious mental and physical health issues. Subsequently, these consequences could also affect their families and the society as a whole.

While the concept of NEETs is often used in policies and academic research to identify the share of young people who are disengaged from the labour market *and* education or training, the concept is also criticized because of its vagueness. For instance, it is mistakenly confused with only joblessness or labour market discouragement, it is lumping different subgroups together, and it is often viewed as an indicator for a social group. However, reasons to be NEET could relate to different experiences, and NEETs can have very different characteristics. Moreover, not all NEETs are equally vulnerable for the long-term consequences. To overcome most of these critiques, I decided to look at three specific groups of vulnerable young people, namely young people with low literacy levels, young mothers and early school-leavers. I analyse this taking two different perspectives: the macro perspective (how institutions frame the risk to become NEET) and the meso and micro perspective (how family resources protect individuals to become NEET).

Main conclusions

There are three main conclusions that can be drawn from this dissertation. The first conclusion is that skills are very important in preventing early school-leaving and becoming NEET. The second conclusion is that financial resources are important in preventing early school-leaving and becoming NEET. The third conclusion is that although we could not do hard causal analysis, our results suggest that it probably will be very hard to re-integrate young people with policy once they are NEET. These conclusions are relevant for academic research because I provide additional evidence on the underlying reasons why certain vulnerable young people are more likely to become NEET, and how the underlying mechanisms work. In addition, the results are also particularly relevant for policy makers.

Lessons for policy makers

Reducing the number of NEETs is an important social challenge in most European societies and the Netherlands. While some policies, for instance (enabling) Active

Labour Market Policies, seem effective in reducing general NEET rates, I find that this does not benefit one of the most vulnerable groups: young people with low literacy skills. There could be several reasons why policy interventions do not reach these more vulnerable groups of young people. First, if the urge for policy makers is to reduce the overall number of NEETs in a country, this could cause an incentive to focus first on the ones with the least problematic problems rather than the ones that are most vulnerable. Second, those most at risk may not always be aware of their need of extra help.

Related to this, policy makers should be aware that there are no cheap solutions for these problems. Take the example of Early Childhood Care and Education (ECEC). Previous research has shown that especially the quality of Early Childhood Care and Education is important for skills development at early ages. My research shows that good and affordable ECEC is important to prevent young mothers to become NEET. However, good quality and affordable ECEC is expensive.

My findings show that low skills levels and low financial resources are important factors to explain NEET and early school-leaving. Since the vulnerable NEETs and early school-leavers are often facing multiple problems to integrate in society, I suggest that a more integral and personalised programme would be most optimal. For young people who are NEET, and thus do not have access to learning opportunities at work or school, I suggest that for instance a neighbourhood coach could help. This professional worker could use different sets of tools to not only help the young people with their skill development, but also with other problems that prevent a successful integration in society. To prevent early school-leaving, I suggest a personalized programme for students at risk. For example, a buddy programme with a role model (e.g., an older student) that makes young people aware of the long-term beneficial impact of certain choices at an early age. At the same time, my research shows that the parents play a major role in educational decision making. Therefore it is important to also improve parental involvement, e.g. by organising parental meetings to improve their understanding about how the education system works and what the advantages of extra schooling are. Subsequently, this may substitute the negative effects of having low-skilled parents or living in low-income families.

Dissemination activities

I will inform researchers and policy makers about the conclusions of this dissertation. In fact, I already presented during my PhD preliminary results on several international and national conferences, an activity that I plan to continue in the future. Furthermore, I also have shared and will share my research by publishing in peer-reviewed international journals. **Chapter 2** ‘The Low Skills trap: The Failure of Education and Social Policies in Preventing Low-Literate Young People from being Long-Term NEET’ is already published in the Journal of Youth Studies. A preliminary version of **Chapter 2** and **Chapter 3** are published in the ROA Research Memorandum. In the

near future, the other chapters presented in this dissertation will also be submitted to high-ranking peer-reviewed journals. To reach a wider audience I will also share my findings on social media.

This dissertation is part of the project ‘Understanding NEETS. Individual and institutional determinants of youth inactivity in France, Germany, Japan, the Netherlands, and the United Kingdom’. Beside the chapters of my dissertation, I also wrote three chapters for the main publication of this project *‘The dynamics of marginalized youth: Not in education, employment, or training around the world’*²⁴ to describe a general overview of cross-national comparisons of NEETs related to education systems, labour market policies and family policies.

²⁴ Levels, M., Brzinsky-Fay, C., Holmes, C., Jongbloed, J., & Taki, H. (2022). *The dynamics of marginalized youth: Not in education, employment, or training around the world*. Routledge - Taylor & Francis Group.

SUMMARY

Different NEETs, different needs?

Explaining why vulnerable young people are more likely to become NEET

This dissertation focuses on explaining why some vulnerable young people in society are more likely to become Not in Employment, Education and Training (NEET) than others. The concept of NEETs is broader than youth unemployment since it also covers young people who are not in education and inactive. The main reason to develop this concept was that a large group of young people disappeared from the radar because they were not included in educational nor in employment statistics because they are often not entitled to unemployment benefits. Being NEET can have detrimental consequences: they are at greater risk of long-term socioeconomic marginalization, criminal careers, unwanted pregnancies, social rejection, and serious mental and physical health issues. Additionally, these consequences do not only affect the NEETs themselves, but also their families and society. Throughout the years, the NEET concept is often used by policymakers to focus on vulnerable young people that lack integration in society.

In this dissertation, I focus on three important groups of vulnerable young people (low-literate young people, young mothers, and early school-leavers) and two different perspectives (macro versus meso/micro). I start this dissertation by taking a macro perspective, in which I focus on the interplay between individuals and their countries' characteristics. In **Chapter 2**, I focus on young people with low literacy skills and their NEET risks, taking into account their countries' education and social policies. I answer the following research questions: *To what extent are low levels of literacy skills associated with a high risk of being long-term NEET? How does this vary cross-nationally? To what extent can cross-national variation be explained by education and social policies?* To answer these research questions, I use data from the Programme for the International Assessment of Adult Competencies [PIAAC] including 25 countries and macro-level indicators on education and social policies. I find that young people with low literacy skills are more likely to become long-term NEETs and that the chances of becoming NEET vary across countries. I find that young people are less likely to become NEET when living in countries with higher (enabling) Active Labour Market Policies (ALMPs) or in social-democratic welfare states. However, it appears higher (enabling) ALMPs and social-democratic welfare states are especially beneficial for young people with higher literacy skills and not for the ones with low literacy skills. Only enforcing ALMPs appear to have a greater impact on young people with low literacy skills than on young people with higher literacy skills. However, given that enforcing ALMPs increase the overall risk that young people are more likely to

become NEET than in education, this is probably not the kind of social policy that policymakers would aim for.

In **Chapter 3**, I focus on young mothers, the affordability of public childcare and subsequent NEET risks. I formulate three research questions: *To what extent do policies that determine the affordability of public childcare (national-level) affect childcare use by young mothers? To what extent does individual-level use of Early Childhood Education and Care (ECEC) reduce young mother's NEET risks?* I use data from the European Union Labour Force Survey [EU-LFS] including the 2010 ad-hoc module 'Reconciliation between work and family life'. I find that the process through which young mothers are more likely to become NEET - in relationship to family policies - can be explained via two stages. First, the results show that young mothers are more likely to use ECEC in countries where childcare is more affordable. Second, young mothers who use ECEC are less likely to become NEET. This implies that lowering the costs of childcare increases the likelihood that young mothers use ECEC and that the actual use of ECEC helps to protect young mothers against NEET risks.

In **Chapter 4** and **Chapter 5**, I move to the other perspective: a micro and meso perspective and I look at individuals and their families. The prime focus is on a group that is highly at risk of being NEET or becoming NEET: early school-leavers. Both chapters focus on the role of parental resources affecting early school-leaving. **Chapter 4** answers the following research question: *What is the relative contribution of different parental resources to children's risk of early school-leaving?* To answer this research question, I use data from the Intergenerational Transmission of Skills [ITS] dataset and data from the Netherlands Cohort Study on Education [NCO]. I find that children's (non-)cognitive skills contribute most to the explained variance of early school-leaving (65%), followed by household income (24%), and other effects of parent's educational attainment (11%). This indicates that parental resources take up 35% of the total explained variance. However, if I consider the indirect effects as well, the total (direct and indirect) effects of parental resources contribute for approximately 53% of the total explained variance. This implies that parental resources are highly relevant in children's risk to become an early school-leaver.

However, sometimes parental resources may change disruptively due to shocks in the family. In **Chapter 5** I use the same dataset as in **Chapter 4** to answer the research questions: *To what extent is the risk of early school-leaving at age 18 in the Netherlands affected by family shocks in the preceding period (age 15-17)? To what extent do skills related to parents' education moderate this relationship?* I focus on three disruptive family events that may change the family dynamics (parental separation, a large drop in the household income, or parents becoming dependent on social welfare) and define these as 'family shocks'. I show that a large income drop has an immediate and strong effect on early school-leaving. However, parental separation and parents becoming dependent on social welfare seem more indicative of a long-term process that may change the family dynamics long before and after the actual shock takes

place. Additionally, it matters who of the parents experiences the shock. I only find a moderating effect of parental education for an income drop: children from medium-educated parents experience a less strong negative effect of the large income drop than children from low-educated parents.

Two broad and overarching conclusions may be drawn from this dissertation. The first conclusion is that skills are important in preventing early school-leaving and becoming NEET. The second conclusion is that financial resources are important in preventing early school-leaving and becoming NEET. However, overcoming the problems that vulnerable NEETs experience are difficult to solve. NEETs, especially the ones that are the most vulnerable, are difficult to reach and, therefore less targeted by policies. Policies that do target them are less effective for this group, at least for the most vulnerable. This makes long-term NEETs a wicked problem.

SAMENVATTING

Verschillende NEETs, verschillende behoeften?

Verklaren waarom kwetsbare jongvolwassenen een grotere kans hebben om NEET te worden

Dit proefschrift richt zich op kwetsbare jongvolwassenen in de samenleving die niet werken, geen opleiding en geen training volgen en de mogelijke verklaringen die daaraan ten grondslag liggen. De gebruikte afkorting hiervoor is ‘NEET’, wat staat voor Not in Employment Education and Training. De definitie NEET is ontstaan doordat een belangrijke groep jongvolwassenen letterlijk uit de officiële statistieken viel. Ze waren niet opgenomen in de onderwijsstatistieken, maar waren ook niet terug te vinden in de werkgelegenheidsstatistieken omdat ze geen recht hadden op werkloosheidsuitkeringen. Echter, voor beleidsmakers was het belangrijk om meer zicht te krijgen op deze groep jongvolwassenen aangezien zij een grotere kans hebben op langdurige sociaaleconomische marginalisering, criminele carrières, onbedoelde zwangerschappen, sociale uitsluiting en ernstige geestelijke en lichamelijke gezondheidsproblemen. Daarnaast worden de negatieve consequenties groter wanneer de periode NEET langer duurt en hebben de negatieve gevolgen ook invloed op hun families en de samenleving.

Ik richt me in het proefschrift op drie belangrijke groepen kwetsbare jongvolwassenen (laaggeletterden, jonge moeders en voortijdig schoolverlaters) en bekijk dit vanuit twee verschillende perspectieven (macro versus meso/micro). Ik begin het proefschrift vanuit een macro-perspectief, waarbij de wisselwerking tussen individuen en specifieke landskenmerken wordt onderzocht. In **Hoofdstuk 2** onderzoek ik de relatie tussen laaggeletterdheid en het risico om NEET te worden. Daarbij kijk ik ook of deze relatie sterker of minder sterk wordt in bepaalde beleidscontexten. De onderzoeksvragen die ik tracht te beantwoorden zijn: *In hoeverre hangt laag-geletterdheid samen met een hoger risico om NEET te worden? Hoe verschilt dit tussen landen? In hoeverre kunnen deze verschillen tussen landen verklaard worden door kenmerken van onderwijs en sociaal beleid?* Om deze onderzoeksvragen te beantwoorden gebruik ik de PIAAC-dataset [Programme for the International Assessment of Adult Competencies] met informatie uit 25 landen. Daarnaast koppel ik ook de benodigde beleidsinformatie op macroniveau aan deze dataset. De resultaten laten zien dat laaggeletterde jongvolwassenen een groter risico hebben om langdurig NEET te worden, maar de sterkte van de relatie verschilt tussen landen. Wat betreft de beleidsmaatregelen ontdek ik dat jongvolwassenen een minder grote kans hebben om NEET te worden wanneer zij in landen leven met een actief arbeidsmarktbeleid (met name gericht op trainingen aanbieden en het combineren van werk en familie) of in sociaaldemocratische

welvaartsstaten. Echter, opvallend is dat dit actieve arbeidsmarktbeleid en het wonen in een sociaaldemocratische welvaartsstaat vooral voordelig is voor hoog-geletterde jongvolwassenen: zij hebben minder risico om NEET te worden. Daarentegen blijkt een forcerend arbeidsmarktbeleid wel te werken specifiek voor laaggeletterden. Het probleem is echter dat een dergelijk beleid de kansen van alle jongvolwassenen vergroot om NEET te zijn in plaats van onderwijs te volgen.

In **Hoofdstuk 3** richt ik mij op jonge moeders, kinderopvangkosten en de risico's om NEET te worden. De volgende onderzoeksvragen komen aan de orde: *In hoeverre hangt (op nationaal niveau) kinderopvangkosten samen met het gebruik ervan door jonge moeders? In hoeverre verlaagt het individueel gebruik van kinderopvang het risico om NEET te worden?* Om dit te onderzoeken gebruik ik data van de European Union Labour Force Survey [EU-LFS] inclusief de 2010 module 'Combineren van werk en familie'. Ik ontdek dat het proces waardoor jonge moeders meer kans hebben om NEET te worden - in relatie tot het gezinsbeleid - kan worden opgedeeld in twee fasen. Ten eerste, jonge moeders hebben een grotere kans om voor- en vroegschoolse educatie en opvang te gebruiken in landen waar de kosten lager zijn. Ten tweede, het gebruik van deze voor- en vroegschoolse educatie en opvang verlaagt vervolgens de kans om NEET te worden. Dit houdt in dat het verlagen van de kosten van kinderopvang de kans vergroot dat jonge moeders kinderopvang gebruiken en dat het daadwerkelijk gebruik van kinderopvang jonge moeders beschermt om NEET te worden.

Voor **Hoofdstuk 4** en **Hoofdstuk 5** verander ik van perspectief, namelijk naar het micro-en meso-perspectief waarin ik kijk naar individuen en hun families. De hoofdfocus ligt op de groep jongvolwassenen die een hoog risico hebben op het zijn of het worden van NEET: de voortijdig schoolverlaters. **Hoofdstuk 4** beantwoordt de volgende onderzoeksvraag: *Wat is de relatieve bijdrage van de verschillende ouderlijke hulpbronnen op het risico dat hun kinderen voortijdig schoolverlaters worden?* Om deze onderzoeksvraag te beantwoorden gebruik ik data van de Intergenerational Transmission of Skills [ITS] dataset en koppel dat aan de data van het Nationaal Cohortonderzoek Onderwijs [NCO]. De resultaten tonen aan dat de (non-)cognitieve vaardigheden van kinderen de grootste bijdragen leveren aan de verklaarde variantie op voortijdig schoolverlaten (65%), gevolgd door het huishoudinkomen (24%) en andere effecten van ouderlijke opleiding (11%). Dit suggereert dat ouderlijke hulpbronnen voor ongeveer 35% bijdragen aan de totale verklaarde variantie. Echter, wanneer ik de indirecte effecten ook meeneem, dragen de ouderlijke hulpbronnen voor ongeveer 53% bij aan de totale verklaarde variantie. Hieruit blijkt dus dat ouderlijke hulpbronnen erg belangrijk zijn voor de kans dat kinderen voortijdig de school verlaten.

Echter, de omvang van ouderlijke hulpbronnen kan ook veranderen als gevolg van familie schokken. In **Hoofdstuk 5** gebruik ik dezelfde dataset als in **Hoofdstuk 4** en beantwoord ik de volgende onderzoeksvragen: *In hoeverre hangt de kans op voortijdig schoolverlaten op 18-jarige leeftijd in Nederland samen met familie schokken in de voorliggende*

periode (leeftijd 15-17)? In hoeverre modereren de vaardigheden van ouders, gerelateerd aan hun opleiding, deze samenhang? Ik richt mij op drie disruptieve familiegebeurtenissen die de dynamiek in de familie kunnen veranderen (het uit elkaar gaan van ouders, een grote inkomensdaling binnen het huishouden, ouders die afhankelijk worden van een uitkering) en definieer deze als ‘familie schokken’. Ik vind dat een grote inkomensdaling een rechtstreeks en sterk effect heeft op voortijdig schoolverlaten. Echter, bij kinderen waarvan de ouders uit elkaar gaan of afhankelijk worden van een uitkering valt op dat de familie dynamiek al is veranderd zowel voor als na de feitelijk schok. Daarnaast doet het ertoe bij wie van de ouders de schok heeft plaatsgevonden. Wat betreft het modererende effect, vind ik enkel dat kinderen met middelbaaropgeleide ouders een minder sterk negatief effect ervaren van de inkomensdaling dan kinderen van laagopgeleide ouders.

Uiteindelijk laat dit proefschrift twee brede en overkoepelende conclusies zien. Namelijk dat zowel vaardigheden als financiële hulpbronnen van belang zijn bij het voorkomen van voortijdig schoolverlaten en NEET. Echter, de problemen voor de kwetsbare NEETs zijn niet eenvoudig op te lossen. NEETs, vooral degene die het meest kwetsbaar zijn, zijn moeilijk te bereiken, waardoor gericht beleid moeilijk is. De beleidsmaatregelen die deze doelgroep wel bereiken, blijken juist minder effectief, althans voor de meest kwetsbaren. Dit maakt langdurig NEET een complex probleem.

APPENDICES

APPENDIX A – SUPPLEMENTARY MATERIALS CHAPTER 2

Table A1 - Descriptive statistics for vocationally educated young people (iscd 3/4)

	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>Min.</i>	<i>Max.</i>
Dependent variables					
NEET	9,021	0.10		0.00	1.00
Employed	9,021	0.77		0.00	1.00
Education/training	9,021	0.13		0.00	1.00
Country-level variables					
Vocational orientation	24	0.60	0.82	-1.84	1.74
Control variables					
Male	9,021	0.55		0.00	1.00
Age	9,021	24.62	3.16	20.00	30.00
Migration status					
Native	9,021	0.91		0.0	1.0
First generation migrant	9,021	0.06		0.0	1.0
Second generation migrant	9,021	0.03		0.0	1.0
Parental education level					
Both parents low educated	9,021	0.13		0.0	1.0
At least one medium educated parent	9,021	0.59		0.0	1.0
At least one higher educated parent	9,021	0.22		0.0	1.0
Missing	9,021	0.05		0.0	1.0
Educational attainment					
Low educated	9,021	0.03		0.0	1.0
Medium educated	9,021	0.97		0.0	1.0
High educated	9,021	0.00		0.0	0.0
Vocational track	9,021	1.00		1.0	1.0
Output gap	25	-0.02	1.03	-3.96	1.26

Table A2 - Descriptive statistics country-level variables

	Vocational orientation	ALMP	Enablement	Enforcement	Welfare state	Output gap
Austria	1.70	0.54	0.54	0.64	Social-democratic	0.16
Belgium	0.95	0.39	0.06	-1.95	Social-democratic	0.48
Canada	-1.72	-0.87	-0.96	1.43	Liberal	0.37
Czech Republic	1.74	-0.72			Transitional	0.32
Denmark	0.45	3.57	1.32	-1.50	Social-democratic	0.34
Estonia	-0.44	-0.97			Transitional	-2.01
Finland	0.74	1.00	0.46	-1.16	Conservative	0.09
France	0.39	0.82	1.17	-0.82	Conservative	0.56
Germany	0.89	0.74	0.14	-0.37	Conservative	0.21
Greece	-0.31				Mediterranean	-3.96
Ireland	-0.35	0.74	-0.33	0.42	Liberal	-0.78
Israel	-0.27	-1.12			Mediterranean	1.03
Italy	0.95	-0.47	-0.25	-0.48	Mediterranean	0.17
Japan	-0.73	-0.82	-0.96	0.30	Conservative	0.32
Korea (rep)	-0.55	-0.77				1.26
Netherlands	1.26	1.27	-0.02	0.64	Social-democratic	0.47
New Zealand		-0.84	-1.36	0.53	Liberal	0.33
Norway	0.89	0.04	1.80	0.08	Social-democratic	0.10
Poland	0.30	0.19			Transitional	0.64
Slovak Republic	1.49	-0.79			Transitional	0.11
Slovenia	1.06	-0.57			Transitional	-1.47
Spain	0.00	0.77	-0.49	-0.48	Mediterranean	-0.69
Sweden	0.69	1.27	1.96	-0.82	Social-democratic	0.30
United Kingdom	0.47	-0.57	-0.33	0.30	Liberal	-0.16
United States	-1.84	-1.17	-1.60	1.99	Liberal	-0.49

Table A3 - Regression estimates on the relationship between low literacy skills and long-term NEET, per country

	Coef.	SD	CI lower 95%	CI upper 95%
Japan	0.027	0.130	-0.228	0.282
Italy	0.049	0.052	-0.053	0.151
Germany	0.055 ~	0.031	-0.006	0.116
United States	0.058	0.039	-0.017	0.134
Korea (rep)	0.061	0.069	-0.076	0.197
Denmark	0.068 ~	0.036	-0.003	0.138
Canada	0.075 ~	0.044	-0.011	0.162
Finland	0.081	0.068	-0.052	0.213
Austria	0.088 ~	0.051	-0.012	0.187
Norway	0.100 *	0.042	0.017	0.182
Czech Republic	0.104	0.070	-0.033	0.240
Belgium	0.107 *	0.044	0.021	0.194
Netherlands	0.108 *	0.051	0.008	0.207
Sweden	0.108 *	0.053	0.004	0.212
Greece	0.112 *	0.044	0.025	0.198
Slovenia	0.125 **	0.042	0.043	0.207
Poland	0.128 ***	0.037	0.056	0.200
Spain	0.130 ***	0.036	0.060	0.200
New Zealand	0.136 ***	0.041	0.055	0.216
Israel	0.143 ***	0.026	0.092	0.193
Estonia	0.155 ***	0.045	0.067	0.243
Ireland	0.164 ***	0.046	0.074	0.255
France	0.175 ***	0.039	0.098	0.252
United Kingdom	0.228 ***	0.045	0.140	0.316
Slovak Republic	0.328 ***	0.062	0.208	0.449

~ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Figure A1 - Margin plots on the relationship between low literacy skills and long-term NEET

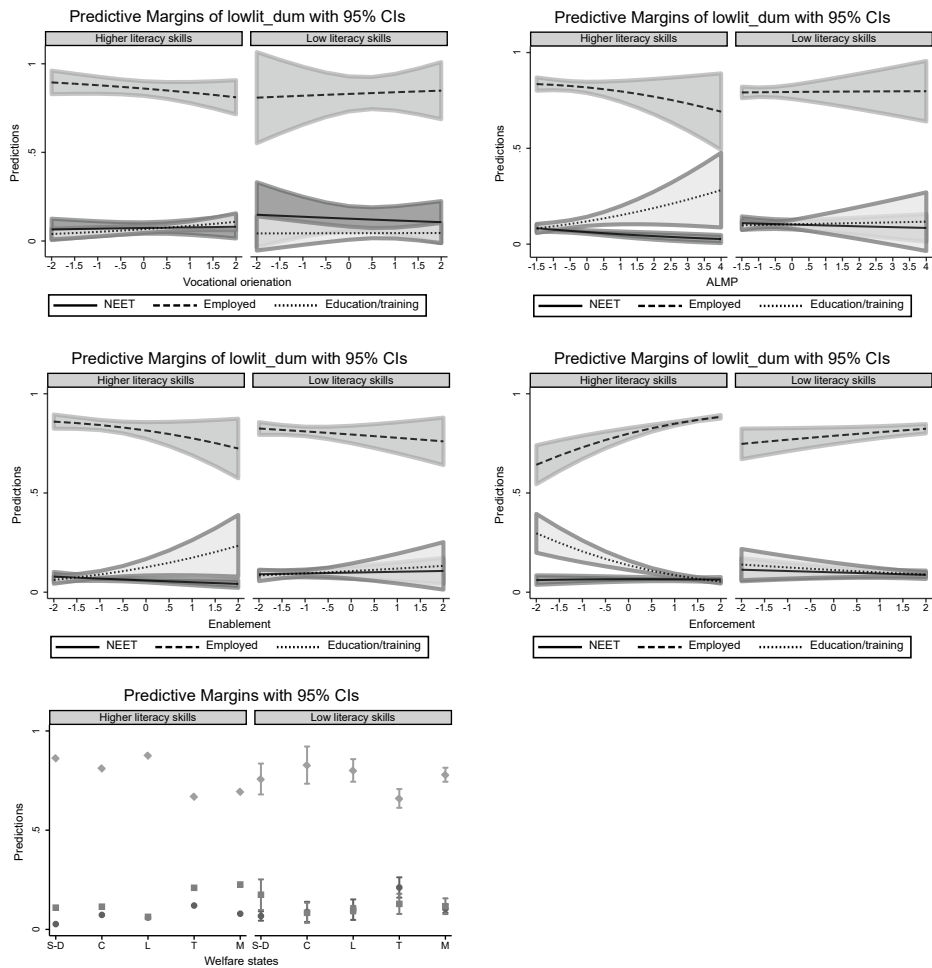


Table A4 - Multinomial regression estimates on the relationship between low literacy skills and long-term NEET, employment versus education/training

Employed	M1a	M1b	M2a	M2b	M3a	M3b	M4a	M4b	M5a	M5b
Low literacy skills (Higher literacy skills=Ref.)	0.639 (0.196)	0.641 (0.200)	0.684* (0.118)	0.623*** (0.086)	0.717~ (0.137)	0.590** (0.113)	0.709~ (0.134)	0.664* (0.132)	0.696* (0.107)	0.332*** (0.093)
Vocational orientation	0.922 (0.215)	0.925 (0.212)								
Low literacy*Vocational orientation		0.979 (0.263)								
ALMP			1.164 (0.131)	1.237~ (0.136)						
Low literacy*ALMP			0.788* (0.081)							
Enablement			1.076 (0.119)			1.155 (0.124)				
Low literacy*Enablement						0.739* (0.084)				
Enforcement							1.093 (0.088)	1.049 (0.092)		
Low literacy*Enforcement								1.136 (0.130)		
Welfare states (Social-Democratic = Ref.)										
Conservative									0.371*** (0.109)	0.313*** (0.104)
Liberal									0.461** (0.125)	0.395*** (0.109)
Transitional									0.161*** (0.036)	0.144*** (0.037)

Missing	(0.979)	(0.973)	(0.427)	(0.427)	(0.425)	(0.427)	(0.384)	(0.381)	(0.326)	(0.310)
	1.006	1.007	1.050	1.048	0.965	0.967	0.924	0.920	0.913	0.913
	(0.253)	(0.253)	(0.110)	(0.112)	(0.144)	(0.139)	(0.133)	(0.130)	(0.079)	(0.078)
Educational attainment (Low educated=Ref.)										
Medium educated	2.243**	2.235**	2.971***	2.950***	2.839***	2.807***	2.734***	2.716***	2.750***	2.761***
	(0.693)	(0.682)	(0.327)	(0.320)	(0.362)	(0.355)	(0.365)	(0.355)	(0.349)	(0.341)
High educated			8.124***	8.138***	7.623***	7.635***	7.403***	7.408***	7.966***	7.979***
			(1.071)	(1.063)	(1.069)	(1.054)	(1.108)	(1.092)	(1.263)	(1.259)
Vocational track (Academic track=Ref.)			1.097	1.101	1.429	1.439	1.461	1.471	1.148	1.144
			(0.234)	(0.235)	(0.383)	(0.386)	(0.382)	(0.386)	(0.242)	(0.250)
Output gap	1.090	1.091	0.671*	0.672*	0.674~	0.682~	0.892	0.877	1.103	1.103
	(0.281)	(0.281)	(0.110)	(0.112)	(0.151)	(0.152)	(0.184)	(0.185)	(0.174)	(0.175)
Education/training	M1a	M1b	M2a	M2b	M3a	M3b	M4a	M4b	M5a	M5b
Low literacy skills (Higher literacy skills=Ref.)	0.418*	0.423*	0.702	0.576***	0.776	0.533*	0.797	0.570*	0.708	0.579
	(0.145)	(0.150)	(0.216)	(0.094)	(0.261)	(0.135)	(0.266)	(0.142)	(0.217)	(0.223)
Vocational orientation	1.217	1.219								
	(0.291)	(0.296)								
Low literacy*Vocational orientation										
ALMP			1.517***	1.654***						
			(0.191)	(0.210)						
Low literacy*ALMP				0.595*						
				(0.147)						
Enablement					1.576*	1.734**				
					(0.281)	(0.310)				
Low literacy*Enablement						0.564*				
						(0.137)				

Enforcement	0.660** (0.091)	0.598*** (0.079)	0.382* (0.156)	0.344* (0.161)
Low literacy*Enforcement		1.722** (0.306)	0.254*** (0.065)	0.209*** (0.057)
Welfare states (Social-Democratic = Ref.)			0.387*** (0.097)	0.377*** (0.106)
Conservative			0.684 (0.192)	0.662 (0.208)
Liberal				0.986 (0.611)
Transitional				2.170 (1.147)
Mediterranean				0.583 (0.261)
Low literacy*Conservative				0.676 (0.326)
Low literacy*Liberal				2.444*** (0.356)
Low literacy*Transitional				0.426** (0.131)
Low literacy*Mediterranean				1.011~ (0.006)
Male (Female=Ref.)	2.455** (0.731)	2.457** (0.735)	2.421*** (0.420)	2.412*** (0.416)
Age	0.746 (0.522)	0.743 (0.518)	0.425* (0.160)	0.430* (0.161)
Age²	1.000 (0.014)	1.000 (0.014)	1.011 (0.007)	1.011 (0.007)
			2.604*** (0.396)	2.412*** (0.416)
			0.521~ (0.201)	0.430* (0.161)
			1.007 (0.007)	1.011 (0.007)
			2.390*** (0.411)	2.451*** (0.358)
			0.445* (0.166)	0.425** (0.131)
			1.010 (0.007)	1.011~ (0.006)

Migration status (Native=Ref.)										
First generation										
migrant	0.663 (0.334)	0.664 (0.342)	1.528 (0.416)	1.546 (0.418)	1.493 (0.443)	1.528 (0.453)	1.573 (0.483)	1.594 (0.483)	1.658 (0.521)	1.636 (0.511)
Second generation										
migrant	2.112* (0.651)	2.118* (0.651)	1.692* (0.381)	1.735* (0.407)	1.635* (0.364)	1.707* (0.387)	1.930*** (0.337)	2.016*** (0.360)	2.013*** (0.350)	2.057*** (0.370)
Parental education level (Both low educated=Ref.)										
At least one medium										
educated parent	1.150 (0.383)	1.150 (0.384)	1.398~ (0.248)	1.400~ (0.251)	1.388 (0.328)	1.386 (0.324)	1.554~ (0.401)	1.539~ (0.390)	1.659* (0.365)	1.653* (0.360)
At least one higher										
educated parent	3.453** (1.591)	3.445** (1.586)	1.774* (0.515)	1.800* (0.518)	1.515 (0.470)	1.545 (0.477)	1.742 (0.603)	1.772~ (0.597)	2.093* (0.757)	2.122* (0.734)
Missing	1.266 (0.894)	1.266 (0.896)	0.901 (0.243)	0.900 (0.243)	0.824 (0.252)	0.833 (0.248)	0.965 (0.306)	0.963 (0.294)	1.282 (0.313)	1.252 (0.297)
Educational attainment (Low educated=Ref.)										
Medium educated	4.894** (2.944)	4.883** (2.921)	3.663*** (1.154)	3.578*** (1.140)	3.336*** (1.067)	3.244*** (1.052)	3.501*** (1.143)	3.366*** (1.102)	3.363*** (0.938)	3.307*** (0.928)
High educated			9.041*** (2.391)	8.957*** (2.371)	9.155*** (2.271)	9.089*** (2.263)	9.385*** (2.446)	9.220*** (2.380)	9.608*** (2.287)	9.551*** (2.233)
Vocational track (Academic track=Ref.)										
			0.581 (0.261)	0.590 (0.269)	0.732 (0.439)	0.746 (0.453)	0.765 (0.444)	0.789 (0.466)	0.651 (0.283)	0.673 (0.307)
Output gap	0.966 (0.304)	0.966 (0.306)	0.956 (0.218)	0.962 (0.227)	0.566 (0.254)	0.579 (0.264)	0.557~ (0.190)	0.538~ (0.186)	1.008 (0.164)	1.007 (0.162)
N country	24	24	24	24	17	17	17	17	24	24
N individual	8,575	8,575	32,720	32,720	19,207	19,207	19,207	19,207	32,489	32,489

p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Standard errors in parentheses; country-level variables are standardized; Odds ratios

~ p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Standard errors in parentheses; country-level variables are standardized; Odds ratios

Table A5 - Multinomial regression estimates on the relationship between low literacy skills and long-term NEET, employment versus education/training – 16 countries

Employed	M1a	M1b	M2a	M2b	M3a	M3b	M4a	M4b	M5a	M5b
Low literacy skills (Higher literacy skills=Ref.)	0.745 (0.374)	0.744 (0.354)	0.728~ (0.139)	0.648** (0.105)	0.720~ (0.139)	0.591** (0.114)	0.712~ (0.136)	0.667* (0.134)	0.732~ (0.132)	0.332*** (0.094)
Vocational orientation	1.306 (0.364)	1.305 (0.377)								
Low literacy*Vocational orientation		1.000 (0.392)								
ALMP			1.223~ (0.149)	1.321* (0.158)						
Low literacy*ALMP				0.751** (0.078)						
Enablement					1.082 (0.122)	1.163 (0.127)				
Low literacy*Enablement						0.737* (0.084)				
Enforcement						1.091 (0.088)	1.048 (0.092)			
Low literacy*Enforcement							1.136 (0.130)			
Welfare states (Social-Democratic = Ref.)										
Conservative									0.373*** (0.111)	0.314*** (0.107)
Liberal									0.246*** (0.077)	0.211*** (0.069)
Mediterranean									0.200*** (0.051)	0.154*** (0.047)
Low literacy*Conservative										2.350~ (1.113)

Low literacy*Liberal	2.009~ (0.779)
Low literacy*Mediterranean	3.073* (1.380)

Education/training	M1a	M1b	M2a	M2b	M3a	M3b	M4a	M4b	M5a	M5b
Low literacy skills (Higher literacy skills=Ref.)	0.420 (0.251)	0.365~ (0.210)	0.809 (0.262)	0.642* (0.122)	0.779 (0.263)	0.535* (0.137)	0.800 (0.269)	0.572* (0.144)	0.812 (0.268)	0.589 (0.228)
Vocational orientation	2.149* (0.720)	2.129* (0.732)								
Low literacy*Vocational orientation		1.333 (0.595)								
ALMP			1.720*** (0.223)	1.917*** (0.251)						
Low literacy*ALMP				0.547** (0.122)						
Enablement					1.592* (0.289)	1.752** (0.317)				
Low literacy*Enablement						0.564* (0.137)				
Enforcement							0.659** (0.092)	0.597*** (0.079)		
Low literacy*Enforcement								1.724** (0.307)		
Welfare states (Social-Democratic = Ref.)										
Conservative									0.380* (0.153)	0.343* (0.159)
Liberal									0.171*** (0.055)	0.145*** (0.050)

[illegible]

~ p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Standard errors in parentheses; country-level variables are standardized; Models are controlled for male, age, age², migration status, parental education level educational attainment and output gap; Odds ratios

Table A6 - Multinomial regression estimates on the relationship between low literacy skills and long-term NEET, employment versus education/training – controlled for youth unemployment rate instead of output gap

Employed	M1a	M1b	M2a	M2b	M3a	M3b	M4a	M4b	M5a	M5b
Low literacy skills (Higher literacy skills=Ref.)	0.770 (0.237)	0.816 (0.252)	0.713~ (0.124)	0.653** (0.093)	0.730 (0.141)	0.600** (0.116)	0.714~ (0.135)	0.675~ (0.139)	0.694* (0.107)	0.327*** (0.091)
Vocational orientation	0.889 (0.197)	0.903 (0.201)								
Low literacy*Vocational orientation		0.843 (0.234)								
ALMP			1.122 (0.189)	1.185 (0.197)						
Low literacy*ALMP				0.798* (0.084)						
Enablement					0.957 (0.098)	1.030 (0.114)				
Low literacy*Enablement						0.738* (0.086)				
Enforcement							1.115 (0.079)	1.079 (0.085)		
Low literacy*Enforcement								1.124 (0.129)		
Welfare states (Social-Democratic = Ref.)										
Conservative									0.369*** (0.099)	0.310*** (0.096)
Liberal									0.459*** (0.100)	0.393*** (0.087)
Transitional									0.188*** (0.041)	0.168*** (0.042)

Mediterranean	0.371** (0.133)	0.297** (0.126)
Low literacy*Conservative	2.399~ (1.144)	2.031~ (0.762)
Low literacy*Liberal	1.660 (0.545)	2.721* (1.136)
Low literacy*Transitional		
Low literacy*Mediterranean		

Education/training	M1a	M1b	M2a	M2b	M3a	M3b	M4a	M4b	M5a	M5b
Low literacy skills (Higher literacy skills=Ref.)	0.451* (0.154)	0.468* (0.158)	0.700 (0.217)	0.575*** (0.094)	0.782 (0.264)	0.526* (0.134)	0.792 (0.266)	0.568* (0.137)	0.707 (0.216)	0.581 (0.222)
Vocational orientation	1.191 (0.295)	1.206 (0.307)								
Low literacy*Vocational orientation		0.893 (0.283)								
ALMP			1.497*** (0.173)	1.624*** (0.183)						
Low literacy*ALMP				0.597* (0.141)						
Enablement					1.300* (0.146)	1.440** (0.171)				
Low literacy*Enablement						0.548* (0.136)				
Enforcement							0.787* (0.083)	0.723** (0.076)		

Low literacy*Enforcement											
1.723** (0.298)											
Welfare states (Social-Democratic = Ref.)											
Conservative											
Liberal											
Transitional											
Mediterranean											
Low literacy*Conservative											
Low literacy*Liberal											
Low literacy*Transitional											
Low literacy*Mediterranean											
N country	24	24	24	24	17	17	17	17	24	24	
N individual	8,575	8,575	32,720	32,720	19,207	19,207	19,207	19,207	32,489	32,489	

- p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Standard errors in parentheses; country-level variables are standardized; Models are controlled for male, age², migration status, parental education level educational attainment and youth unemployment rate; Odds ratios

Table A7 - Multinomial regression estimates on the relationship between low literacy skills (at or below level 2) and long-term NEET, employment versus education/training

Employed	M1a	M1b	M2a	M2b	M3a	M3b	M4a	M4b	M5a	M5b
Low literacy skills (Higher literacy skills=Ref.)	0.735 (0.154)	0.779 (0.145)	0.628** (0.108)	0.554*** (0.074)	0.615* (0.133)	0.480*** (0.099)	0.614* (0.132)	0.525*** (0.084)	0.649** (0.108)	0.324** (0.121)
Vocational orientation	0.910 (0.213)	1.136 (0.275)								
Low literacy*Vocational orientation		0.665* (0.115)								
ALMP			1.158 (0.127)	1.382** (0.172)						
Low literacy*ALMP				0.756* (0.103)						
Enablement					1.084 (0.125)	1.350* (0.191)				
Low literacy*Enablement						0.701* (0.110)				
Enforcement							1.090 (0.085)	0.917 (0.078)		
Low literacy*Enforcement								1.288** (0.118)		
Welfare states (Social-Democratic = Ref.)										
Conservative									0.372*** (0.110)	0.229** (0.110)
Liberal									0.484** (0.127)	0.296** (0.126)
Transitional									0.165*** (0.037)	0.113*** (0.049)

Mediterranean										0.317*** (0.093)	0.306* (0.147)
Low literacy*Conservative											2.398* (0.982)
Low literacy*Liberal											2.271~ (1.034)
Low literacy*Transitional											1.906 (0.780)
Low literacy*Mediterranean											1.257 (0.522)
Education/training	M1a	M1b	M2a	M2b	M3a	M3b	M4a	M4b	M5a	M5b	
Low literacy skills (Higher literacy skills=Ref.)	0.464~ (0.180)	0.486 (0.219)	0.538*** (0.088)	0.467*** (0.067)	0.537** (0.108)	0.406*** (0.097)	0.549** (0.112)	0.435*** (0.102)	0.545*** (0.092)	0.356* (0.158)	
Vocational orientation	1.183 (0.299)	1.469 (0.522)									
Low literacy*Vocational orientation		0.695 (0.298)									
ALMP			1.500** (0.193)	1.824*** (0.293)							
Low literacy*ALMP				0.715~ (0.126)							
Enablement					1.585* (0.290)	2.012*** (0.417)					
Low literacy*Enablement					0.659* (0.120)						
Enforcement											
Low literacy*Enforcement							0.661** (0.092)	0.523*** (0.075)			
Welfare states (Social-Democratic = Ref.)								1.490** (0.168)			

Conservative	0.384*	0.265*
Liberal	(0.161)	(0.163)
Transitional	0.276***	0.164***
Mediterranean	(0.071)	(0.071)
	0.405***	0.312*
	(0.099)	(0.144)
	0.749	0.925
	(0.211)	(0.440)
Low literacy*Conservative		1.622
		(0.839)
Low literacy*Liberal		2.228
		(1.147)
Low literacy*Transitional		1.328
		(0.647)
Low literacy*Mediterranean		0.697
		(0.327)
N country	24	24
N individual	8,575	32,489

~ p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Standard errors in parentheses; country-level variables are standardized; Models are controlled for male, age, age², migration status, parental education level educational attainment and output gap; Odds ratios

APPENDIX B - SUPPLEMENTARY MATERIALS CHAPTER 3

Table B1 - OLS estimates of the relation between motherhood & NEET (Figure 2.2)

Country	Coef.	SD	95% Conf.Interval	
Hungary	0.00	0.02	-0.04	0.03
Slovenia	0.09 **	0.03	0.04	0.15
Lithuania	0.10 **	0.03	0.04	0.16
Latvia	0.10 *	0.05	0.01	0.19
Estonia	0.11 **	0.03	0.04	0.18
Belgium	0.15 ***	0.02	0.11	0.20
Portugal	0.16 ***	0.02	0.11	0.20
Ireland	0.17 ***	0.01	0.14	0.20
Romania	0.19 ***	0.02	0.16	0.23
Cyprus	0.20 ***	0.03	0.13	0.27
France	0.21 ***	0.02	0.17	0.25
Spain	0.22 ***	0.02	0.19	0.26
Czech Republic	0.24 ***	0.02	0.20	0.27
Netherlands	0.25 ***	0.02	0.22	0.28
Luxembourg	0.26 ***	0.03	0.20	0.33
United Kingdom	0.26 ***	0.01	0.24	0.29
Bulgaria	0.26 ***	0.02	0.22	0.31
Greece	0.28 ***	0.02	0.24	0.32
Poland	0.28 ***	0.01	0.26	0.31
Italy	0.31 ***	0.02	0.28	0.34
Austria	0.32 ***	0.02	0.28	0.35
Slovak Republic	0.34 ***	0.02	0.29	0.38
Germany	0.34 ***	0.02	0.30	0.38

* p<0.05, ** p<0.01, *** p<0.001; Standard errors in parentheses; Models are based on women aged 20-29; Models are controlled for age, education level and migration background

Table B2 - Parameter estimates for the relationship between childcare costs and NEET, including Oster bounds – including missing data

	M1	M2	M3
Net childcare costs – incl. missings	0.04* (0.02)	0.03 (0.02)	0.03 (0.03)
Net childcare costs - missing (No missing=Ref.)	-0.07** (0.02)	-0.09* (0.04)	-0.11 (0.06)
Education level (Low=ref.)			
Medium educated	-0.22*** (0.02)	-0.21*** (0.02)	-0.21*** (0.02)
High educated	-0.35*** (0.03)	-0.35*** (0.03)	-0.35*** (0.03)
Age 25-29 (Age 20-24=ref.)	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)
Migration background (Native=ref.)	0.14*** (0.03)	0.12*** (0.03)	0.13*** (0.02)
Maternity leave (Weeks)		0.00 (0.02)	0.00 (0.02)
Paid parental leave (Months)		-0.03 (0.03)	-0.04 (0.03)
Unemployment rate (2010)			-0.01 (0.01)
GDP			-0.01 (0.02)
Seats women in parliament			-0.00 (0.02)
Seats religious in parliament			0.00 (0.02)
Constant	1.07*** (0.11)	1.07*** (0.09)	1.08*** (0.09)
$\tilde{R}$ -squared	0.09	0.10	0.10
<i>N</i> young mothers	13,912	13,912	13,912
<i>N</i> country	23	23	23
<i>Oster Method:</i>			
$\tilde{\beta}$ when $\delta = 0$	0.04	0.03	0.03
$\tilde{\beta}$ when $\delta = 1$ and <i>R</i> max is 1.3	0.05	0.03	0.05
$\tilde{\beta}$ when $\delta = 1$ and <i>R</i> max is 2.0	0.07	0.05	0.99
$\tilde{\beta}$ when $\delta = 1$ and <i>R</i> max is 3.0	0.10	0.08	3.73

Note: * p<0.05, ** p<0.01, *** p<0.001

Table B3 - Parameter estimates for the relationship between childcare costs and use of ECEC, including Oster bounds – including missing data

	M1	M2	M3
Net childcare costs – incl. missings	-0.05* (0.02)	-0.05* (0.02)	-0.09* (0.03)
Net childcare costs - missing (No missing=Ref.)	0.10*** (0.02)	0.08* (0.03)	0.11 (0.06)
Education level (Low=ref.)			
Medium educated	0.04* (0.02)	0.04* (0.02)	0.04* (0.02)
High educated	0.09** (0.03)	0.10*** (0.03)	0.10*** (0.02)
Age 25-29 (Age 20-24=ref.)	0.02*** (0.00)	0.02*** (0.00)	0.02*** (0.00)
Migration background (Native=ref.)	-0.02 (0.02)	-0.02 (0.02)	-0.03* (0.02)
Maternity leave (Weeks)		-0.04** (0.01)	-0.04 (0.02)
Paid parental leave (Months)		0.01 (0.02)	-0.02 (0.04)
Unemployment rate (2010)			0.01 (0.02)
GDP			-0.03 (0.04)
Seats women in parliament			-0.02 (0.03)
Seats religious in parliament			0.08 (0.05)
Constant	-0.25*** (0.05)	-0.21** (0.06)	-0.16* (0.07)
$\tilde{R}$ -squared	0.03	0.04	0.05
<i>N</i> young mothers	13,819	13,819	13,819
<i>N</i> country	23	23	23
<i>Oster Method:</i>			
$\tilde{\beta}$ when $\delta = 0$	-0.05	-0.05	-0.09
$\tilde{\beta}$ when $\delta = 1$ and <i>R</i> max is 1.3	-0.05	-0.05	-0.13
$\tilde{\beta}$ when $\delta = 1$ and <i>R</i> max is 2.0	-0.06	-0.06	-0.32
$\tilde{\beta}$ when $\delta = 1$ and <i>R</i> max is 3.0	-0.07	-0.09	-0.65

Note: * p<0.05, ** p<0.01, *** p<0.001

Table B4 - Parameter estimates for the relationship between use of ECEC and subsequent NEET risks, including Oster bounds – including missing data

	M1	M2	M3	M4
Use of ECEC (No=ref.)	-0.23*** (0.03)	-0.22*** (0.03)	-0.22*** (0.03)	-0.22*** (0.03)
Education level (Low=ref.)				
Medium educated	-0.20*** (0.02)	-0.21*** (0.02)	-0.20*** (0.02)	-0.21*** (0.02)
High educated	-0.32*** (0.03)	-0.33*** (0.03)	-0.33*** (0.03)	-0.33*** (0.03)
Age 25-29 (Age 20-24=ref.)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
Migration background (Native=ref.)	0.13** (0.03)	0.13** (0.04)	0.12*** (0.03)	0.13*** (0.03)
Net childcare costs – incl. missings		0.03 (0.02)	0.02 (0.02)	0.01 (0.03)
Net childcare costs - missing (No missing=Ref.)		-0.04 (0.03)	-0.08 (0.04)	-0.08 (0.06)
Maternity leave (Weeks)			-0.01 (0.02)	-0.01 (0.02)
Paid parental leave (Months)			-0.03 (0.03)	-0.04 (0.04)
Unemployment rate (2010)				-0.01 (0.01)
GDP				-0.02 (0.02)
Seats women in parliament				-0.01 (0.03)
Seats religious in parliament				0.02 (0.03)
Constant	1.03*** (0.10)	1.02*** (0.10)	1.03*** (0.09)	1.05*** (0.09)
$\tilde{R}$ -squared	0.13	0.13	0.13	0.14
<i>N</i> young mothers	13,819	13,819	13,819	13,819
<i>N</i> country	23	23	23	23
<i>Oster Method:</i>				
$\tilde{\beta}$ when $\delta = 0$	-0.23	-0.22	-0.22	-0.22
$\tilde{\beta}$ when $\delta = 1$ and <i>R</i> max is 1.3	-0.22	-0.20	-0.20	-0.21
$\tilde{\beta}$ when $\delta = 1$ and <i>R</i> max is 2.0	-0.18	-0.16	-0.16	-0.16
$\tilde{\beta}$ when $\delta = 1$ and <i>R</i> max is 3.0	-0.13	-0.10	-0.09	-0.09

Note: * p<0.05, ** p<0.01, *** p<0.001

Table B5 - Parameter estimates for the relationship between childcare costs and NEET, including Oster bounds – including young mothers aged 15-19

	M1	M2	M3
Net childcare costs - single hh	0.04* (0.02)	0.03 (0.02)	0.03 (0.03)
Education level (Low=ref.)			
Medium educated	-0.21*** (0.02)	-0.21*** (0.02)	-0.21*** (0.02)
High educated	-0.35*** (0.03)	-0.34*** (0.03)	-0.34*** (0.03)
Age (15-19=ref.)			
Age 20-24	0.04 (0.05)	0.04 (0.05)	0.04 (0.05)
Age 25-29	-0.05 (0.05)	-0.05 (0.05)	-0.05 (0.05)
Migration background (Native=ref.)	0.09*** (0.02)	0.08*** (0.02)	0.09*** (0.01)
Maternity leave (Weeks)		0.00 (0.02)	0.00 (0.02)
Paid parental leave (Months)		-0.04 (0.03)	-0.04 (0.03)
Unemployment rate (2010)			-0.01 (0.01)
GDP			-0.01 (0.02)
Seats women in parliament			-0.01 (0.02)
Seats religious in parliament			0.01 (0.03)
Constant	0.64*** (0.06)	0.64*** (0.06)	0.65*** (0.07)
$\tilde{R}$ -squared	0.09	0.10	0.10
<i>N</i> young mothers	14,201	14,201	14,201
<i>N</i> country	22	22	22
<i>Oster Method:</i>			
$\tilde{\beta}$ when $\delta = 0$	0.04	0.03	0.03
$\tilde{\beta}$ when $\delta = 1$ and $R_{\max}$ is 1.3	0.05	0.03	0.04
$\tilde{\beta}$ when $\delta = 1$ and $R_{\max}$ is 2.0	0.07	0.05	1.19
$\tilde{\beta}$ when $\delta = 1$ and $R_{\max}$ is 3.0	0.09	0.08	4.63

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B6 - Parameter estimates for the relationship between childcare costs and use of ECEC, including Oster bounds – including young mothers aged 15-19

	M1	M2	M3
Net childcare costs - single hh	-0.05* (0.02)	-0.05* (0.02)	-0.09* (0.03)
Education level (Low=ref.)			
Medium educated	0.04* (0.02)	0.04* (0.02)	0.04* (0.02)
High educated	0.09** (0.03)	0.10** (0.03)	0.11*** (0.02)
Age (15-19=ref.)			
Age 20-24	0.07** (0.03)	0.06* (0.03)	0.06* (0.03)
Age 25-29	0.17*** (0.03)	0.15*** (0.03)	0.14*** (0.03)
Migration background (Native=ref.)	-0.01 (0.01)	-0.01 (0.01)	-0.02* (0.01)
Maternity leave (Weeks)		-0.04** (0.01)	-0.04 (0.02)
Paid parental leave (Months)		0.01 (0.02)	-0.02 (0.04)
Unemployment rate (2010)			0.01 (0.02)
GDP			-0.02 (0.04)
Seats women in parliament			-0.02 (0.03)
Seats religious in parliament			0.08 (0.05)
Constant	0.08** (0.03)	0.10** (0.03)	0.15** (0.05)
$\tilde{R}$ -squared	0.03	0.04	0.06
<i>N</i> young mothers	14,107	14,107	14,107
<i>N</i> country	22	22	22
<i>Oster Method:</i>			
$\tilde{\beta}$ when $\delta = 0$	-0.05	-0.05	-0.09
$\tilde{\beta}$ when $\delta = 1$ and $R_{\max}$ is 1.3	-0.05	-0.05	-0.13
$\tilde{\beta}$ when $\delta = 1$ and $R_{\max}$ is 2.0	-0.06	-0.06	-0.32
$\tilde{\beta}$ when $\delta = 1$ and $R_{\max}$ is 3.0	-0.07	-0.09	-0.66

Note: * p<0.05, ** p<0.01, *** p<0.001

Table B7 - Parameter estimates for the relationship between use of ECEC and subsequent NEET risks, including Oster bounds – including young mothers aged 15-19

	M1	M2	M3	M4
Use of ECEC (No=ref.)	-0.23*** (0.03)	-0.22*** (0.03)	-0.22*** (0.03)	-0.23*** (0.03)
Education level (Low=ref.)				
Medium educated	-0.20*** (0.02)	-0.20*** (0.02)	-0.20*** (0.02)	-0.20*** (0.02)
High educated	-0.31*** (0.03)	-0.33*** (0.03)	-0.32*** (0.03)	-0.32*** (0.03)
Age (15-19=ref.)				
Age 20-24	0.06 (0.05)	0.06 (0.05)	0.06 (0.05)	0.06 (0.05)
Age 25-29	-0.02 (0.05)	-0.01 (0.05)	-0.02 (0.05)	-0.02 (0.05)
Migration background (Native=ref.)	0.08** (0.02)	0.09** (0.02)	0.08*** (0.02)	0.08*** (0.02)
Net childcare costs - single hh		0.03 (0.02)	0.02 (0.02)	0.01 (0.03)
Maternity leave (Weeks)			-0.00 (0.02)	-0.01 (0.02)
Paid parental leave (Months)			-0.03 (0.03)	-0.04 (0.04)
Unemployment rate (2010)				-0.01 (0.01)
GDP				-0.02 (0.02)
Seats women in parliament				-0.01 (0.03)
Seats religious in parliament				0.02 (0.03)
Constant	0.66*** (0.06)	0.66*** (0.07)	0.66*** (0.06)	0.69*** (0.07)
$\tilde{R}$ -squared	0.13	0.13	0.13	0.13
N young mothers	14,107	14,107	14,107	14,107
N country	22	22	22	22
<i>Oster Method:</i>				
$\tilde{\beta}$ when $\delta = 0$	-0.23	-0.22	-0.22	-0.23
$\tilde{\beta}$ when $\delta = 1$ and Rmax is 1.3	-0.21	-0.20	-0.20	-0.21
$\tilde{\beta}$ when $\delta = 1$ and Rmax is 2.0	-0.18	-0.16	-0.15	-0.16
$\tilde{\beta}$ when $\delta = 1$ and Rmax is 3.0	-0.12	-0.09	-0.08	-0.09

Note: * p<0.05, ** p<0.01, *** p<0.001

APPENDIX C – SUPPLEMENTARY MATERIALS CHAPTER 4

Table C1 - Goodness of fit model shown in Figure 3.1

	Value
TLI	0.976
CFI	0.991
SRMR	0.010
RMSEA	0.041

Table C2 - Goodness of fit for model shown in Figure 3.2

	Value
TLI	0.982
CFI	0.963
SRMR	Not reported because of missing values
RMSEA	0.041

Table C3 - Parental resources, children's skills and early school-leaving (ESL)

	Direct effects		Indirect effects		Total effects	
	Coef.	Std. Coef.	Coef.	Std. Coef.	Coef.	Std. Coef.
Early school-leaver						
Parent's educational attainment	-0.004 **	-0.021	-0.004 ***	-0.021	-0.007 ***	-0.042
Household income	-0.008 ***	-0.051	-0.001 ***	-0.005	-0.009 ***	-0.056
Child's initial cognitive skills	-0.026 ***	-0.118			-0.026 ***	-0.118
Parent's initial cognitive skills			-0.016 ***	-0.071	-0.016 ***	-0.071
Household income						
Parent's educational attainment	0.147 ***	0.141			0.147 ***	0.141
Parent's initial cognitive skills	0.113 ***	0.084	0.112 ***	0.084	0.225 ***	0.168
Child's initial cognitive skills						
Parent's educational attainment	0.085 ***	0.112	0.005 ***	0.006	0.090 ***	0.118
Household income	0.032 ***	0.043			0.032 ***	0.043
Parent's initial cognitive skills	0.347 ***	0.353	0.072 ***	0.074	0.419 ***	0.427
Child's math skills						
Parent's educational attainment			0.090 ***	0.090	0.090 ***	0.090
Household income			0.032 ***	0.033	0.032 ***	0.033
Child's initial cognitive skills	1.000 ***	0.767			1.000 ***	0.767
Parent's initial cognitive skills			0.419 ***	0.327	0.419 ***	0.327
Child's language skills						
Parent's educational attainment			0.096 ***	0.099	0.096 ***	0.099
Household income			0.034 ***	0.036	0.034 ***	0.036
Child's initial cognitive skills	1.072 ***	0.837			1.072 ***	0.837
Parent's initial cognitive skills			0.449 ***	0.357	0.449 ***	0.357
Parent's math skills						
Parent's initial cognitive skills	1.000	0.769			1.000	0.769
Parent's language skills						

Parent's initial cognitive skills	0.996 ***	0.787	0.996 ***	0.787
Parent's educational attainment				
Parent's initial cognitive skills	0.764 ***	0.594	0.764 ***	0.594
Error variances				
Parent's educational attainment	0.648	0.661		
Early school-leaver	0.979	0.983		
Household income	0.959	0.964		
Child's math skills	0.412	0.433		
Child's language skills	0.299	0.323		
Parent's math skills	0.408	0.423		
Parent's language skills	0.380	0.395		
Child's initial cognitive skills	0.807	0.819		
Parent's initial cognitive skills	I			
N	21,863			

Note: *** p<0.001, ** p<0.010, * p<0.050

Table C4 - Parental resources, children's skills and early school-leaving, including residual of teacher advice

	Direct effects		Indirect effects		Total effects	
	Coef.	Std. Coef.	Coef.	Std. Coef.	Coef.	Std. Coef.
<i>Early school-leaver</i>						
Parent's educational attainment	-0.005 **	-0.025	-0.005 ***	-0.025	-0.009 ***	-0.051
Household income	-0.009 ***	-0.056	-0.001 ***	-0.007	-0.010 ***	-0.063
Parent's initial cognitive skills			-0.017 ***	-0.075	-0.017 ***	-0.075
Parent's residual of teacher advice			-0.003 ***	-0.016	-0.003 ***	-0.016
Child's initial cognitive skills	-0.026 ***	-0.118			-0.026 ***	-0.118
Child's residual of teacher advice	-0.006 **	-0.032			-0.006 **	-0.032
<i>Household income</i>						
Parent's educational attainment	0.138 ***	0.124			0.138 ***	0.124
Parent's initial cognitive skills	0.146 ***	0.106	0.092 ***	0.067	0.238 ***	0.173
Parent's residual of teacher advice	0.019	0.019	0.031 ***	0.031	0.051 ***	0.050
<i>Child's initial cognitive skills</i>						
Parent's educational attainment	0.100 ***	0.123	0.005 ***	0.006	0.105 ***	0.129
Household income	0.037 ***	0.051			0.037 ***	0.051
Parent's initial cognitive skills	0.348 ***	0.347	0.076 ***	0.075	0.424 ***	0.422
Parent's residual of teacher advice			0.024 ***	0.033	0.024 ***	0.033
<i>Child's residual of teacher advice</i>						
Parent's educational attainment	0.096 ***	0.091	0.003 *	0.003	0.099 ***	0.094
Household income	0.022 *	0.024			0.022 *	0.024
Parent's initial cognitive skills			0.069 ***	0.054	0.069 ***	0.054
Parent's residual of teacher advice	0.060 ***	0.063	0.023 ***	0.024	0.083 ***	0.087
<i>Child's math skills</i>						
Parent's educational attainment			0.105 ***	0.099	0.105 ***	0.099
Household income			0.037 ***	0.039	0.037 ***	0.039
Child's initial cognitive skills	1.000 ***	0.771			1.000 ***	0.771

Parent's initial cognitive skills		0.424 ***	0.326	0.424 ***	0.326
Parent's residual of teacher advice		0.024 ***	0.025	0.024 ***	0.025
<i>Child's language skills</i>					
Parent's educational attainment		0.112 ***	0.108	0.112 ***	0.108
Household income		0.040 ***	0.043	0.040 ***	0.043
Child's initial cognitive skills	1.068 ***		0.838		0.838
Parent's initial cognitive skills		0.453 ***	0.354	0.453 ***	0.354
Parent's residual of teacher advice		0.026 ***	0.028	0.026 ***	0.028
<i>Parent's math skills</i>					
Parent's initial cognitive skills	1.000 ***		0.765	1.000 ***	0.765
<i>Parent's language skills</i>					
Parent's initial cognitive skills	1.036 ***		0.810	1.036 ***	0.810
<i>Parent's educational attainment</i>					
Parent's initial cognitive skills	0.669 ***		0.542	0.669 ***	0.542
Parent's residual of teacher advice	0.226 ***		0.247	0.226 ***	0.247
Parent's educational attainment	0.577		0.590		
Early school-leaver	0.978		0.982		
Household income	0.958		0.964		
Child's residual of teacher advice	0.982		0.985		
Child's math skills	0.411		0.432		
Child's language skills	0.300		0.325		
Parent's math skills	0.405		0.420		
Parent's language skills	0.379		0.394		
Child's initial cognitive skills	0.813		0.825		
Parent's residual of teacher advice	1.000				
Parent's initial cognitive skills	1.000				
<i>N</i>	21,863				

Note: *** p<0.001, ** p<0.010, * p<0.050; Including missing values on parent's and child's residual of teacher advice

Table C5 - Parental resources, children's skills and early school-leaving, including residual of teacher advice – GSEM logit

	Coef.
<i>Early school-leaver</i>	
Parent's educational attainment	0.160 **
Household income	-0.289 ***
Child's initial cognitive skills	0.792 ***
Child's residual of teacher advice	0.203 ***
<i>Household income</i>	
Parent's educational attainment	0.136 ***
Parent's initial cognitive skills	0.121 ***
Parent's residual of teacher advice	0.026 ***
<i>Parent's educational attainment</i>	
Parent's initial cognitive skills	0.758 ***
Parent's residual of teacher advice	0.253 ***
<i>Child's initial cognitive skills</i>	
Parent's educational attainment	0.093 ***
Household income	0.032 ***
Parent's initial cognitive skills	0.332 ***
<i>Child's math skills</i>	
Child's initial cognitive skills	1.000
<i>Child's language skills</i>	
Child's initial cognitive skills	1.069 ***
<i>Parent's math skills</i>	
Parent's initial cognitive skills	1.000
<i>Parent's language skills</i>	
Parent's initial cognitive skills	0.994 ***
<i>N</i>	21,863

Note: *** $p < 0.001$, ** $p < 0.010$, * $p < 0.050$; Including missing values on parent's and child's residual of teacher advice

Table C6 - Parental resources, children's skills and early school-leaving, including residual of teacher advice – different family structures

	Mothers (M)		Fathers (F)		Daughters (D)		Sons (S)		M+D		M+S		F+D		F+S	
	Std. Coef.		Std. Coef.		Std. Coef.		Std. Coef.		Std. Coef.		Std. Coef.		Std. Coef.		Std. Coef.	
Early school-leaver																
Parent's educational attainment	-0.025 *		-0.008		-0.017		-0.019		-0.020		-0.034 *		-0.015		-0.005	
Household income	-0.056 ***		-0.043 ***		-0.048 ***		-0.055 ***		-0.054 ***		-0.060 ***		-0.040 **		-0.048 **	
Child's initial cognitive skills	-0.118 ***		-0.121 ***		-0.112 ***		-0.122 ***		-0.109 ***		-0.123 ***		-0.116 ***		-0.120 ***	
Child's residual of teacher advice	-0.032 **		-0.037 **		-0.028 **		-0.037 ***		-0.017		-0.043 **		-0.041 **		-0.031 *	
Household income																
Parent's educational attainment	0.124 ***		0.146 ***		0.133 ***		0.128 ***		0.123 ***		0.124 ***		0.147 ***		0.146 ***	
Parent's initial cognitive skills	0.106 ***		0.064 ***		0.085 ***		0.095 ***		0.093 ***		0.120 ***		0.070 **		0.056 **	
Parent's residual of teacher advice	0.019 *		0.033 **		0.027 **		0.024 *		0.012		0.026		0.044 **		0.021	
Child's initial cognitive skills																
Parent's educational attainment	0.123 ***		0.134 ***		0.122 ***		0.114 ***		0.127 ***		0.116 ***		0.136 ***		0.128 ***	
Household income	0.051 ***		0.037 **		0.052 ***		0.033 **		0.057 ***		0.041 **		0.046 **		0.026	
Parent's initial cognitive skills	0.347 ***		0.316 ***		0.334 ***		0.336 ***		0.343 ***		0.337 ***		0.302 ***		0.321 ***	
Child's residual of teacher advice																
Parent's educational attainment	0.091 ***		0.105 ***		0.100 ***		0.097 ***		0.090 ***		0.094 ***		0.110 ***		0.101 ***	
Household income	0.024 *		0.019		0.014		0.031 **		0.014		0.035 *		0.014		0.026 *	
Parent's initial cognitive skills																
Parent's residual of teacher advice	0.063 ***		0.065 ***		0.067 ***		0.061 ***		0.063 ***		0.064 ***		0.073 ***		0.058 ***	
Child's math skills																
Child's initial cognitive skills	0.771 ***		0.762 ***		0.791 ***		0.779 ***		0.801 ***		0.772 ***		0.778 ***		0.784 ***	
Child's language skills																
Child's initial cognitive skills	0.838 ***		0.836 ***		0.862 ***		0.858 ***		0.863 ***		0.861 ***		0.863 ***		0.855 ***	
Parent's math skills																
Parent's initial cognitive skills	0.765 ***		0.794 ***		0.760 ***		0.782 ***		0.752 ***		0.779 ***		0.780 ***		0.808 ***	

Parent's language skills	0.810	***	0.801	***	0.792	***	0.784	***	0.821	***	0.800	***	0.798	***	0.805
Parent's initial cognitive skills															
Parent's educational attainment	0.542	***	0.635	***	0.596	***	0.593	***	0.545	***	0.539	***	0.638	***	0.632
Parent's initial cognitive skills															
Parent's residual of teacher advice	0.247	***	0.279	***	0.260	***	0.266	***	0.245	***	0.249	***	0.277	***	0.282
<i>N</i>	11,707		10,156		11,030		10,833		5,943		5,764		5,087		5,069

Note: *** p<0.001, ** p<0.010, * p<0.050

APPENDIX D – SUPPLEMENTARY MATERIALS CHAPTER 5

Table D1 - Percentage of school-leavers per year

Year turning age 18		Early school-leaver	No early school-leaver	Total
2012	<i>N</i>	2,225	109	2,334
	%	95.33	4.67	100.00
2013	<i>N</i>	2,385	65	2,45
	%	97.35	2.65	100.00
2014	<i>N</i>	2,64	63	2,703
	%	97.67	2.33	100.00
2015	<i>N</i>	2,664	74	2,738
	%	97.30	2.70	100.00
2016	<i>N</i>	2,812	62	2,874
	%	97.84	2.16	100.00
2017	<i>N</i>	2,867	82	2,949
	%	97.22	2.78	100.00
2018	<i>N</i>	2,915	95	3,01
	%	96.84	3.16	100.00
2019	<i>N</i>	2,902	94	2,996
	%	96.86	3.14	100.00
Total	<i>N</i>	21,41	644	22,054
	%	97.08	2.92	100.00

Table D2 - Descriptive statistics – Income drop of at least 25%

	Age 15-17				Age 19-21					
	N	Mean	SD	Min.	Max.	N	Mean	SD	Min.	Max.
Early school-leaver (No=ref.)	22,018	0.027		0.000	1.000	15,821	0.025		0.000	1.000
Income drop of at least 25% (No=ref.)	22,018	0.035		0.000	1.000	15,821	0.164		0.000	1.000
Initial cognitive skills parent	22,018	0.156	0.857	-2.514	2.225	15,821	0.143	0.854	-2.514	2.225
Educational attainment parent (Low=ref.)	22,018	0.179		0.000	1.000	15,821	0.187		0.000	1.000
Medium	22,018	0.463		0.000	1.000	15,821	0.476		0.000	1.000
High	22,018	0.359		0.000	1.000	15,821	0.337		0.000	1.000
Higher education other parent (Other=ref.)	22,018	0.287		0.000	1.000	15,821	0.261		0.000	1.000
Household income at age 12-14	22,018	0.134	0.963	-3.531	1.408	15,821	0.102	0.969	-3.531	1.408
Initial cognitive skills child	22,018	0.100	0.856	-3.621	1.783	15,821	0.099	0.855	-3.621	1.788
Female (Male=ref.)	22,018	0.505		0.000	1.000	15,821	0.504		0.000	1.000
Migrant (Native=ref.)	22,018	0.058		0.000	1.000	15,821	0.056		0.000	1.000

Technical note: Income drop of at least 25% between age 19 and 21 is a dummy whether there was a significant drop in the household income of at least 25 points in the national household percentile ranking between age 19 and age 21. If no data was accessible of the age 21, we compared the age 19 with 21. Moreover, all children that turned 18 in 2018 or 2019 are not included since we do not have data after the year 2019. This means that we do not have two national household percentiles to compare to calculate the income drop.

Table D3 - Descriptive statistics – Parents receive benefits

	Age 15-17					Age 19-21				
	N	Mean	SD	Min.	Max.	N	Mean	SD	Min.	Max.
Early school-leaver (No=ref.)	22,018	0.029		0.000	1.000	19,025	0.029		0.000	1.000
On benefits (No=ref.)	22,018	0.798		0.000	1.000	19,025	0.792		0.000	1.000
Yes	22,018	0.149		0.000	1.000	19,025	0.148		0.000	1.000
Missing	22,018	0.053		0.000	1.000	19,025	0.061		0.000	1.000
Initial cognitive skills parent	22,018	0.156	0.857	-2.514	2.225	19,025	0.148	0.856	-2.514	2.225
Educational attainment parent (Low=ref.)	22,018	0.179		0.000	1.000	19,025	0.184		0.000	1.000
Medium	22,018	0.463		0.000	1.000	19,025	0.470		0.000	1.000
High	22,018	0.358		0.000	1.000	19,025	0.346		0.000	1.000
Higher education other parent (Other=ref.)	22,018	0.286		0.000	1.000	19,025	0.274		0.000	1.000
Household income at age 12-14	22,018	0.130	0.968	-3.531	1.408	19,025	0.116	0.972	-3.531	1.408
Initial cognitive skills child	22,018	0.097	0.857	-3.621	1.783	19,025	0.099	0.856	-3.621	1.788
Female (Male=ref.)	22,018	0.505		0.000	1.000	19,025	0.503		0.000	1.000
Migrant (Native=ref.)	22,018	0.058		0.000	1.000	19,025	0.058		0.000	1.000

Technical note: For the dummy whether one of the parents of the child received benefits when the child was aged 19-21, while none of the parents received benefits when the child was aged 16-18, we left out children that turned 18 in 2019 because we could not measure the benefit status of age 19 or further for them since we only have data until 2019.

Table D4 - Descriptive statistics – Parental separation

	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>Min.</i>	<i>Max.</i>	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>Min.</i>	<i>Max.</i>
Early school-leaver (No=ref.)	22,018	0.029		0.000	1.000	22,018	0.029		0.000	1.000
Separation (No=ref.)	22,018	0.775		0.000	1.000	22,018	0.522		0.000	1.000
Yes	22,018	0.051		0.000	1.000	22,018	0.036		0.000	1.000
Unknown	22,018	0.175		0.000	1.000	22,018	0.442		0.000	1.000
Initial cognitive skills parent	22,018	0.156	0.857	-2.514	2.225	22,018	0.156	0.857	-2.514	2.225
Educational attainment parent (Low=ref.)	22,018	0.179		0.000	1.000	22,018	0.179		0.000	1.000
Medium	22,018	0.463		0.000	1.000	22,018	0.463		0.000	1.000
High	22,018	0.358		0.000	1.000	22,018	0.358		0.000	1.000
Higher education other parent (Other=ref.)	22,018	0.286		0.000	1.000	22,018	0.286		0.000	1.000
Household income at age 12-14	22,018	0.130	0.968	-3.531	1.408	22,018	0.130	0.968	-3.531	1.408
Initial cognitive skills child	22,018	0.097	0.857	-3.621	1.788	22,018	0.097	0.857	-3.621	1.788
Female (Male=ref.)	22,018	0.505		0.000	1.000	22,018	0.505		0.000	1.000
Migrant (Native=ref.)	22,018	0.058		0.000	1.000	22,018	0.058		0.000	1.000

Technical note: For the measurement of parental separation at age 19-21 we looked at whether the parents separate when the child was aged 19-21. For this age group, we left out children that turned 18 in 2019 because we could not measure whether their parents separated after age 18 since we only have data until 2019.

Table D5 - Descriptive statistics – Income drop and on benefits for fathers and mothers separately

	Age 15-17				Age 19-21			
	N	Mean	Min.	Max.	N	Mean	Min.	Max.
Income drop of at least 25% - Father (No=ref.)	20,061	0.034	0.000	1.000	11,456	0.031	0.000	1.000
Income drop of at least 25% - Mother (No=ref.)	20,357	0.038	0.000	1.000	11,711	0.037	0.000	1.000
On benefits - Father (No=ref.)	10,261	0.878	0.000	1.000	10,261	0.741	0.000	1.000
Yes	10,261	0.063	0.000	1.000	10,261	0.050	0.000	1.000
Missing	10,261	0.059	0.000	1.000	10,261	0.208	0.000	1.000
On benefits - Mother (No=ref.)	11,793	0.845	0.000	1.000	11,793	0.732	0.000	1.000
Yes	11,793	0.088	0.000	1.000	11,793	0.071	0.000	1.000
Missing	11,793	0.068	0.000	1.000	11,793	0.197	0.000	1.000

Table D6 - Logistic regression estimates on the relationship between an income drop of at least 10% and early school-leaving (age 15-17)

	M0	M1	M2	M3
Income drop of at least 10% (No=ref.)		0.693 *** (0.119)	0.684 *** (0.120)	0.874 *** (0.209)
Initial cognitive skills parent	-0.020 (0.057)	-0.021 (0.057)	-0.010 (0.061)	-0.021 (0.057)
Income drop of at least 10% * Initial cognitive skills parent			-0.070 (0.138)	
Educational attainment parent (Low=ref.)				
Medium	-0.249 ** (0.103)	-0.249 ** (0.104)	-0.249 ** (0.104)	-0.191 * (0.112)
High	-0.303 ** (0.137)	-0.305 ** (0.137)	-0.305 ** (0.137)	-0.297 ** (0.147)
Income drop of at least 10% * Medium-educated parent				-0.383 (0.278)
Income drop of at least 10% * High-educated parent				-0.041 (0.315)
Higher education other parent (Other=ref.)	-0.395 *** (0.122)	-0.406 *** (0.122)	-0.406 *** (0.122)	-0.407 *** (0.122)
Household income at age 12-14	-0.168 *** (0.042)	-0.155 *** (0.043)	-0.156 *** (0.043)	-0.156 *** (0.043)
Initial cognitive skills child	-0.628 *** (0.047)	-0.626 *** (0.047)	0.626 *** (0.047)	0.626 *** (0.047)
Female (Male=ref.)	-0.390 *** (0.086)	-0.398 *** (0.086)	-0.398 *** (0.086)	-0.395 *** (0.086)
Migrant (Native=ref.)	0.389 ** (0.158)	0.372 ** (0.158)	0.372 ** (0.158)	0.375 ** (0.158)
Constant	-3.259 *** (0.099)	-3.331 *** (0.100)	-3.330 *** (0.100)	-3.362 *** (0.106)
<i>N</i>	21,820	21,820	21,820	21,820

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses

Table D7 - Logistic regression estimates on the relationship between an income drop of at least 25% and early school-leaving (age 15-17) – including year-dummies

	M0	M1	M2	M3
Income drop of at least 25% (No=ref.)		0.889 *** (0.161)	0.845 *** (0.170)	1.282 *** (0.276)
Initial cognitive skills parent	-0.631 *** (0.047)	-0.630 *** (0.047)	-0.629 *** (0.047)	-0.630 *** (0.047)
Income drop of at least 25% * Initial cognitive skills parent			-0.211 (0.190)	
Educational attainment parent (Low=ref.)				
Medium	-0.239 ** (0.104)	-0.245 ** (0.104)	-0.245 ** (0.104)	-0.186 * (0.108)
High	-0.280 ** (0.138)	-0.294 ** (0.138)	-0.293 ** (0.138)	-0.276 ** (0.143)
Income drop of at least 25% * Medium-educated parent				-0.802 (0.385)
Income drop 125% * High-educated parent				-0.200 (0.409)
Higher education other parent (Other=ref.)	-0.0239 (0.057)	-0.018 (0.057)	-0.002 (0.059)	-0.017 (0.057)
Initial cognitive skills child	-0.370 *** (0.123)	-0.369 *** (0.123)	-0.369 *** (0.123)	-0.369 *** (0.123)
Household income at age 12-14	-0.171 *** (0.043)	-0.163 *** (0.043)	-0.164 *** (0.043)	-0.168 *** (0.043)
Female (Male=ref.)	-0.393 *** (0.086)	-0.395 *** (0.086)	-0.396 *** (0.086)	-0.395 *** (0.086)
Migrant (Native=ref.)	0.371 ** (0.158)	0.365 ** (0.158)	0.367 ** (0.158)	0.362 ** (0.158)
Year of turning 18 (2012=ref.)				
2013	-0.660 *** (0.171)	-0.668 *** (0.171)	0.670 *** (0.171)	-0.669 *** (0.171)
2014	-0.657 *** (0.169)	-0.676 *** (0.169)	-0.681 *** (0.169)	-0.682 *** (0.169)
2015	-0.491 *** (0.161)	-0.523 *** (0.161)	-0.525 *** (0.161)	-0.527 *** (0.161)
2016	-0.772 *** (0.174)	-0.792 *** (0.174)	-0.793 *** (0.174)	-0.798 *** (0.174)
2017	-0.416 *** (0.157)	-0.436 *** (0.157)	-0.437 *** (0.157)	-0.434 *** (0.157)
2018	-0.309 ** (0.152)	-0.327 ** (0.152)	-0.316 ** (0.152)	-0.320 ** (0.152)
2019	-0.310 ** (0.152)	-0.327 ** (0.152)	0.330 ** (0.152)	-0.334 ** (0.152)

	(0.153)	(0.154)	(0.154)	(0.154)
Constant	.2845 ***	-2.869 ***	-2.866 ***	-2.900 ***
	(0.133)	(0.133)	(0.133)	(0.135)
<i>N</i>	21,820	21,820	21,820	21,820

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses

Table D8 - Logistic regression estimates on the relationship between an income drop of at least 25% and early school-leaving (age 19-21)

	M0	M1	M2	M3
Income drop of at least 25% (No=ref.)		0.053 (0.159)	-0.001 (0.166)	-0.061 (0.314)
Initial cognitive skills parent	-0.096 (0.070)	-0.097 (0.070)	-0.059 (0.073)	-0.097 (0.070)
Income drop of at least 25% * Initial cognitive skills parent			-0.315 * (0.185)	
Educational attainment parent (Low=ref.)				
Medium	-0.293 ** (0.119)	-0.294 ** (0.119)	-0.294 ** (0.119)	-0.329 *** (0.126)
High	-0.575 *** (0.174)	-0.578 *** (0.174)	-0.572 *** (0.174)	-0.534 *** (0.182)
Income drop of at least 25% * Medium-educated parent				0.316 (0.378)
Income drop of at least 25% * High-educated parent				-0.234 (0.479)
Higher education other parent (Other=ref.)	-0.462 *** (0.163)	-0.464 *** (0.163)	-0.460 *** (0.163)	-0.459 *** (0.163)
Household income at age 12-14	-0.12 ** (0.052)	-0.12 ** (0.052)	-0.119 ** (0.052)	-0.12 ** (0.052)
Initial cognitive skills child	-0.68 *** (0.057)	-0.681 *** (0.057)	-0.678 *** (0.057)	-0.682 *** (0.057)
Female (Male=ref.)	-0.304 *** (0.103)	-0.307 *** (0.104)	-0.304 *** (0.104)	-0.308 *** (0.104)
Migrant (Native=ref.)	0.439 ** (0.194)	0.44 ** (0.194)	0.445 ** (0.194)	0.44 ** (0.194)
Constant	-3.32 *** (0.117)	-3.325 *** (0.117)	-3.318 *** (0.117)	-3.315 *** (0.119)
<i>N</i>	15,821	15,821	15,821	15,821

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses

Table D9 - Logistic regression estimates on the relationship between an income drop of at least 25% and early school-leaving (age 15-17 and 19-21) – only children included that turned 18 between 2013 and 2017

	15-17			19-21				
	Mo	Mr	M2	M3	Mo	Mr	M2	M3
Income drop of at least 25% (No=ref.)		0.89 *** (0.208)	0.885 *** (0.218)	1.496 *** (0.339)		0.0736 (0.186)	0.00530 (0.196)	-0.223 (0.435)
Initial cognitive skills parent	-0.087 (0.078)	-0.076 (0.078)	-0.074 (0.081)	-0.074 (0.078)	-0.143 * (0.080)	-0.143 * (0.080)	-0.099 (0.083)	-0.144 * (0.080)
Income drop of at least 25% * Initial cognitive skills parent			-0.019 (0.244)				-0.371 * (0.215)	
Educational attainment parent (Low=ref.)								
Medium	-0.125 (0.141)	-0.135 (0.141)	-0.135 (0.141)	-0.0329 (0.148)	-0.108 (0.142)	-0.109 (0.142)	-0.110 (0.142)	-0.165 (0.149)
High	-0.286 (0.191)	-0.306 (0.191)	-0.306 (0.191)	-0.260 (0.201)	-0.277 (0.195)	-0.281 (0.196)	-0.276 (0.195)	-0.250 (0.203)
Income drop of at least 25% * Medium-educated parent				-1.175 ** (0.491)				0.572 (0.496)
Income drop of at least 25% * High-educated parent				-0.399 (0.536)				-0.042 (0.579)
Higher education other parent (Other=ref.)	-0.324 * (0.168)	-0.320 * (0.168)	-0.320 * (0.168)	-0.321 * (0.168)	-0.331 * (0.172)	-0.334 * (0.173)	-0.329 * (0.172)	-0.329 * (0.172)

Household income at age 12-14	-0.21 *** (0.056)	-0.204 *** (0.056)	-0.204 *** (0.056)	-0.211 *** (0.056)	-0.233 *** (0.057)	-0.233 *** (0.057)	-0.231 *** (0.057)	-0.233 *** (0.057)
Initial cognitive skills child	-0.651 *** (0.064)	-0.652 *** (0.064)	-0.652 *** (0.064)	-0.656 *** (0.064)	-0.627 *** (0.065)	-0.629 *** (0.065)	-0.626 *** (0.065)	-0.631 *** (0.065)
Female (Male=ref.)	-0.399 *** (0.117)	-0.406 *** (0.118)	-0.406 *** (0.118)	-0.401 *** (0.118)	-0.332 *** (0.119)	-0.336 *** (0.120)	-0.333 *** (0.120)	-0.337 *** (0.120)
Migrant (Native=ref.)	0.607 *** (0.206)	0.613 *** (0.206)	0.613 *** (0.207)	0.613 *** (0.207)	0.501 ** (0.217)	0.504 ** (0.217)	0.508 ** (0.217)	0.505 ** (0.217)
Constant	-3.542 *** (0.138)	-3.582 *** (0.138)	-3.582 *** (0.138)	-3.65 *** (0.145)	-3.606 *** (0.141)	-3.612 *** (0.142)	-3.604 *** (0.141)	-3.591 *** (0.143)
<i>N</i>	13,603	13,603	13,603	13,603	13,515	13,515	13,515	13,515

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses

Table D10 - Logistic regression estimates on the relationship between parents receiving benefits and early school-leaving (age 15-17) – including year-dummies

	M0	M1	M2	M3
On benefits (No=ref.)				
Yes		0.513 *** (0.102)	0.518 *** (0.103)	0.470 ** (0.188)
Missing		1.547 *** (0.188)	1.548 *** (0.189)	1.743 *** (0.245)
Initial cognitive skills parent	-0.017 (0.055)	-0.040 (0.055)	-0.053 (0.067)	-0.036 (0.055)
On benefits * Initial cognitive skills parent			0.039 (0.115)	
Missing * Initial cognitive skills parent			0.023 (0.144)	
Educational attainment parent (Low=ref.)				
Medium	-0.220 ** (0.099)	-0.180 * (0.100)	-0.180 * (0.100)	-0.103 (0.129)
High	-0.296 ** (0.133)	-0.245 * (0.134)	-0.244 * (0.134)	-0.289 * (0.162)
On benefits * Medium-educated parent				-0.112 (0.237)
On benefits * High-educated parent				0.399 (0.267)
Missing * Medium-educated parent				-0.317 (0.266)
Missing * High-educated parent				-0.441 (0.413)
Higher education other parent (Other=ref.)	-0.399 *** (0.119)	-0.321 *** (0.120)	-0.32 *** (0.120)	-0.336 *** (0.121)
Household income at age 12-14	-0.186 *** (0.040)	-0.159 *** (0.042)	-0.159 *** (0.042)	-0.159 *** (0.042)
Initial cognitive skills child	-0.624 *** (0.045)	-0.611 *** (0.045)	-0.611 *** (0.045)	-0.611 *** (0.045)
Female (Male=ref.)	-0.343 *** (0.082)	-0.357 *** (0.082)	-0.356 *** (0.082)	-0.357 *** (0.083)
Migrant (Native=ref.)	0.489 *** (0.144)	0.445 *** (0.146)	0.44 *** (0.146)	0.448 *** (0.146)
Year of turning 18 (2012=ref.)				
2013	-0.576 *** (0.162)	0.246 (0.210)	0.247 (0.210)	0.251 (0.211)
2014	-0.623 *** (0.163)	0.211 (0.212)	0.211 (0.212)	0.212 (0.213)

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2015	-0.464 *** (0.156)	0.36 * (0.206)	0.361 * (0.206)	0.361 * (0.206)
2016	-0.729 *** (0.167)	0.099 (0.215)	0.099 (0.215)	0.095 (0.216)
2017	-0.374 ** (0.152)	0.441 ** (0.203)	0.442 ** (0.203)	0.438 ** (0.204)
2018	-0.263 * (0.146)	0.538 *** (0.198)	0.538 *** (0.197)	0.533 *** (0.198)
2019	-0.254 * (0.147)	0.566 *** (0.200)	0.566 *** (0.200)	0.557 *** (0.200)
Constant	-2.835 *** (0.129)	-3.82 *** (0.193)	-3.822 *** (0.193)	-3.841 *** (0.202)
<i>N</i>	22,018	22,018	22,018	22,018

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses

Table D11 - Logistic regression estimates on the relationship between parents receiving benefits and early school-leaving (age 19-21)

	M0	M1	M2	M3
On benefits (No=ref.)				
Yes		0.483 *** (0.112)	0.441 *** (0.118)	0.405 ** (0.204)
Missing		1.304 *** (0.126)	1.312 *** (0.126)	1.460 *** (0.203)
Initial cognitive skills parent	-0.055 (0.059)	-0.080 (0.060)	-0.058 (0.073)	-0.078 (0.060)
On benefits * Initial cognitive skills parent			-0.167 (0.131)	
Missing * Initial cognitive skills parent			0.091 (0.145)	
Educational attainment parent (Low=ref.)				
Medium	-0.217 ** (0.105)	-0.163 (0.106)	-0.170 (0.106)	-0.165 (0.138)
High	-0.453 *** (0.147)	-0.351 ** (0.149)	-0.362 ** (0.149)	-0.280 (0.176)
On benefits * Medium-educated parent				0.219 (0.252)
On benefits * High-educated parent				-0.186 (0.335)
Missing * Medium-educated parent				-0.254 (0.270)
Missing * High-educated parent				-0.214 (0.404)
Higher education other parent (Other=ref.)	-0.396 *** (0.132)	-0.244 * (0.134)	-0.232 * (0.134)	-0.249 * (0.135)
Household income at age 12-14	-0.183 *** (0.043)	-0.172 *** (0.045)	-0.171 *** (0.045)	-0.172 *** (0.045)
Initial cognitive skills child	-0.637 *** (0.049)	-0.634 *** (0.049)	-0.634 *** (0.049)	-0.632 *** (0.049)
Female (Male=ref.)	-0.328 *** (0.089)	-0.353 *** (0.089)	-0.354 *** (0.089)	-0.353 *** (0.089)
Migrant (Native=ref.)	0.631 *** (0.149)	0.573 *** (0.151)	0.574 *** (0.151)	0.575 *** (0.151)
Constant	-3.244 *** (0.102)	-3.540 *** (0.111)	-3.533 *** (0.111)	-3.554 *** (0.126)
<i>N</i>	19,025	19,025	19,025	19,025

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses

Table D12 - Logistic regression estimates on the relationship between parents receiving benefits and early school-leaving (age 15-17 and 19-21) – without missing category

15-17					19-21			
	M ₀	M ₁	M ₂	M ₃	M ₀	M ₁	M ₂	M ₃
On benefits (No=ref.)		0.496 *** (0.102)	0.502 *** (0.104)	0.451 ** (0.188)		0.452 *** (0.113)	0.413 *** (0.118)	0.370 * (0.204)
Initial cognitive skills parent	-0.045 (0.059)	-0.045 (0.059)	-0.058 (0.067)	-0.044 (0.059)	-0.104 (0.065)	-0.104 (0.065)	-0.060 (0.074)	-0.104 (0.065)
On benefits * Initial cognitive skills parent			0.043 (0.115)				-0.164 (0.131)	
Educational attainment parent (Low=ref.)								
Medium	-0.116 (0.110)	-0.107 (0.110)	-0.106 (0.110)	-0.079 (0.129)	-0.081 (0.118)	-0.073 (0.118)	-0.074 (0.118)	-0.136 (0.138)
High	-0.112 (0.142)	-0.111 (0.142)	-0.109 (0.142)	-0.221 (0.164)	-0.227 (0.160)	-0.230 (0.160)	-0.237 (0.160)	-0.196 (0.178)
On benefits * Medium-educated parent				-0.120 (0.237)				0.223 (0.253)
On benefits * High-educated parent				0.407 (0.267)				-0.186 (0.336)
Higher education other parent (Other=ref.)	-0.320 *** (0.121)	-0.322 *** (0.122)	-0.323 *** (0.122)	-0.324 *** (0.122)	-0.293 ** (0.138)	-0.289 ** (0.138)	-0.287 ** (0.138)	-0.289 ** (0.138)
Household income at age 12-14	-0.257 *** (0.042)	-0.212 *** (0.043)	-0.212 *** (0.043)	-0.212 *** (0.043)	-0.277 *** (0.046)	-0.246 *** (0.047)	-0.245 *** (0.047)	-0.246 *** (0.047)
Initial cognitive skills child	-0.615 *** (0.049)	-0.603 *** (0.049)	-0.603 *** (0.049)	-0.605 *** (0.049)	-0.632 *** (0.054)	-0.623 *** (0.054)	-0.622 *** (0.054)	-0.622 *** (0.054)

Female (Male=ref.)	-0.379 *** (0.089)	-0.385 *** (0.089)	-0.385 *** (0.089)	-0.384 *** (0.089)	-0.384 *** (0.098)	-0.391 *** (0.098)	-0.393 *** (0.098)	-0.391 *** (0.098)
Migrant (Native=ref.)	0.492 *** (0.154)	0.443 *** (0.155)	0.444 *** (0.155)	0.443 *** (0.155)	0.597 *** (0.164)	0.547 *** (0.165)	0.547 *** (0.165)	0.546 *** (0.165)
Constant	-3.438 *** (0.107)	-3.535 *** (0.110)	-3.537 *** (0.110)	-3.522 *** (0.120)	-3.512 *** (0.117)	-3.597 *** (0.119)	-3.589 *** (0.119)	-3.573 *** (0.129)
N	20,857	20,857	20,857	20,857	17,873	17,873	17,873	17,873

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses

Table D13 - Logistic regression estimates on the relationship between parents receiving benefits and early school-leaving (age 15-17 and 19-21) – only children included that turned 18 between 2013 and 2017

	Age 15-17				Age 19-21			
	Mo	Mr	M2	M3	Mo	Mr	M2	M3
On benefits (No=ref.)		0.533 *** (0.132)	0.444 *** (0.136)	0.671 *** (0.228)		0.561 *** (0.129)	0.525 *** (0.136)	0.496 *** (0.235)
Missing		2.833 *** (0.303)	2.580 *** (0.332)	0.452 (1.075)		2.886 *** (0.278)	2.684 *** (0.295)	1.488 *** (0.679)
Initial cognitive skills parent	-0.0936 (0.0745)	-0.13 (0.0753)	-0.179 ** (0.088)	-0.145 * (0.076)	-0.094 (0.075)	-0.133 * (0.076)	-0.127 (0.089)	-0.149 ** (0.076)
On benefits * Initial cognitive skills parent			0.07 (0.152)				-0.129 (0.153)	
Missing * Initial cognitive skills parent			0.747 ** (0.330)				0.597 ** (0.293)	
Educational attainment parent (Low=ref.)								
Medium	-0.0577 (0.135)	-0.0336 (0.137)	-0.043 (0.137)	-0.005 (0.165)	-0.058 (0.135)	-0.024 (0.138)	-0.039 (0.137)	-0.126 (0.166)
High	-0.257 (0.184)	-0.239 (0.186)	-0.257 (0.187)	-0.304 (0.219)	-0.257 (0.184)	-0.223 (0.187)	-0.253 (0.187)	-0.255 (0.216)
On benefits * Medium-educated parent				-0.328 (0.293)				0.153 (0.291)
On benefits * High-educated parent				0.0953 (0.363)				-0.109 (0.380)
Missing * Medium-educated parent				2.889 ** (1.146)				1.783 ** (0.777)
Missing * High-educated parent				2.795 ** (1.210)				1.774 ** (0.848)

Higher education other parent (Other=ref.)	-0.340 (0.161)	**	-0.278 (0.162)	*	-0.259 (0.162)	-0.266 (0.162)	-0.340 (0.161)	**	-0.282 (0.162)	*	-0.264 (0.162)	-0.275 (0.162)	*
Initial cognitive skills child	-0.631 (0.061)	***	-0.599 (0.062)	***	-0.599 (0.062)	-0.610 (0.062)	-0.631 (0.061)	***	-0.597 (0.062)	***	-0.598 (0.062)	-0.600 (0.062)	***
Household income	-0.225 (0.053)	***	-0.186 (0.055)	***	-0.190 (0.055)	-0.184 (0.055)	-0.225 (0.053)	***	-0.206 (0.055)	***	-0.208 (0.055)	-0.208 (0.055)	***
Female (Male=ref.)	-0.335 (0.112)	***	-0.311 (0.113)	***	-0.318 (0.113)	-0.323 (0.113)	-0.335 (0.112)	***	-0.031 (0.113)	***	-0.316 (0.113)	-0.316 (0.113)	***
Migrant (Native=ref.)	0.67 (0.191)	***	0.623 (0.195)	***	0.614 (0.196)	0.611 (0.196)	0.67 (0.191)	***	0.543 (0.197)	***	0.547 (0.197)	0.547 (0.197)	***
Constant	-3.522 (0.134)	***	-3.714 (0.140)	***	-3.712 (0.140)	-3.718 (0.156)	-3.522 (0.134)	***	-3.741 (0.142)	***	-3.729 (0.141)	-3.686 (0.154)	***
N	13,692		13,692		13,692	13,692	13,692		13,692		13,692	13,692	

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses

Table D14 - Logistic regression estimates on the relationship between parental separation and early school-leaving (age 15-17) – including year-dummies

	M0	M1	M2	M3
Separation (No=ref.)				
Yes		0.601 *** (0.161)	0.604 *** (0.161)	0.735 ** (0.293)
Unknown		0.776 *** (0.101)	0.773 *** (0.102)	0.585 *** (0.174)
Initial cognitive skills parent	-0.017 (0.055)	-0.031 (0.055)	-0.039 (0.067)	-0.030 (0.055)
Separation * Initial cognitive skills parent			0.179 (0.192)	
Separation unknown * Initial cognitive skills parent			-0.013 (0.104)	
Educational attainment parent (Low=ref.)				
Medium	-0.220 ** (0.099)	-0.229 ** (0.100)	-0.228 ** (0.100)	-0.303 ** (0.126)
High	-0.296 ** (0.133)	-0.357 *** (0.133)	-0.356 *** (0.133)	-0.441 *** (0.162)
Separation*Medium-educated parent				-0.181 (0.374)
Separation*High-educated parent				-0.193 (0.449)
Separation unknown*Medium-educated parent				0.261 (0.210)
Separation unknown*High-educated parent				0.290 (0.249)
Higher education other parent (Other=ref.)	-0.399 *** (0.119)	-0.427 *** (0.119)	-0.428 *** (0.119)	-0.427 *** (0.119)
Household income at age 12-14	-0.186 *** (0.040)	-0.035 (0.045)	-0.035 (0.045)	-0.034 (0.045)
Initial cognitive skills child	-0.624 *** (0.045)	-0.617 *** (0.045)	-0.618 *** (0.045)	-0.616 *** (0.045)
Female (Male=ref.)	-0.343 *** (0.082)	-0.353 *** (0.082)	-0.353 *** (0.082)	-0.353 *** (0.082)
Migrant (Native=ref.)	0.489 *** (0.144)	0.428 *** (0.145)	0.425 *** (0.145)	0.431 *** (0.145)
Year of turning 18 (2012=ref.)				
2013	-0.576 *** (0.162)	-0.572 *** (0.163)	-0.569 *** (0.163)	-0.578 *** (0.163)
2014	-0.623 *** (0.163)	-0.634 *** (0.164)	-0.630 *** (0.164)	-0.636 *** (0.164)
2015	-0.464 *** (0.156)	-0.485 *** (0.156)	-0.485 *** (0.156)	-0.486 *** (0.156)

2016	-0.729 *** (0.167)	-0.742 *** (0.168)	-0.74 *** (0.168)	-0.744 *** (0.168)
2017	-0.374 ** (0.152)	-0.394 *** (0.152)	-0.392 *** (0.152)	-0.396 *** (0.152)
2018	-0.263 * (0.146)	-0.282 * (0.147)	-0.280 * (0.147)	-0.276 * (0.147)
2019	-0.254 * (0.147)	-0.292 ** (0.148)	-0.288 * (0.148)	-0.295 ** (0.148)
Constant	-2.835 *** (0.129)	-3.002 *** (0.132)	-3.004 *** (0.132)	-2.945 *** (0.141)
<i>N</i>	22,018	22,018	22,018	22,018

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses

Table D15 - Logistic regression estimates on the relationship between parental separation and early school-leaving (age 19-21)

	Mo	M1	M2	M3
Separation (No=ref.)				
Yes		0.604 *** (0.196)	0.566 *** (0.203)	0.308 (0.408)
Unknown		0.599 *** (0.088)	0.586 *** (0.089)	0.619 *** (0.158)
Initial cognitive skills parent	-0.013 (0.055)	-0.0252 (0.055)	0.0587 (0.078)	-0.0234 (0.055)
Separation * Initial cognitive skills parent			-0.245 (0.248)	
Separation unknown * Initial cognitive skills parent			-0.137 (0.099)	
Educational attainment parent (Low=ref.)				
Medium	-0.230 ** (0.100)	-0.239 ** (0.099)	-0.243 ** (0.099)	-0.295 ** (0.147)
High	-0.317 ** (0.132)	-0.386 *** (0.133)	-0.385 *** (0.133)	-0.275 (0.186)
Separation*Medium-educated parent				0.495 (0.484)
Separation*High-educated parent				0.150 (0.598)
Separation unknown*Medium-educated parent				0.0595 (0.197)
Separation unknown*High-educated parent				-0.215 (0.235)
Higher education other parent (Other=ref.)	-0.419 *** (0.118)	-0.468 *** (0.119)	-0.463 *** (0.119)	-0.461 *** (0.119)
Household income at age 12-14	-0.183 *** (0.040)	-0.103 ** (0.042)	-0.101 ** (0.042)	-0.101 ** (0.042)
Initial cognitive skills child	-0.622 *** (0.045)	-0.648 *** (0.045)	-0.646 *** (0.045)	-0.646 *** (0.045)
Female (Male=ref.)	-0.342 *** (0.082)	-0.394 *** (0.082)	-0.394 *** (0.082)	-0.394 *** (0.082)
Migrant (Native=ref.)	0.507 *** (0.144)	0.466 *** (0.144)	0.468 *** (0.144)	0.462 *** (0.144)
Constant	-3.21 *** (0.0955)	-3.46 *** (0.104)	-3.449 *** (0.104)	-3.455 *** (0.126)
<i>N</i>	22,018	22,018	22,018	22,018

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses

Table D16 - Logistic regression estimates on the relationship between parental separation and early school-leaving (age 15-17 and 19-21) – only children included that turned 18 between 2013 and 2017

	15-17			19-21				
	M0	M1	M2	M3	M0	M1	M2	M3
Separation (No=ref.)								
Yes		0.845 *** (0.199)	0.876 *** (0.199)	0.896 ** (0.381)		0.857 *** (0.244)	0.807 *** (0.259)	-0.193 (0.739)
Unknown		0.79 *** (0.136)	0.824 *** (0.138)	0.642 *** (0.244)		0.773 *** (0.123)	0.771 *** (0.125)	0.985 *** (0.225)
Initial cognitive skills parent	-0.0936 (0.0745)	-0.107 (0.075)	-0.203 ** (0.094)	-0.107 (0.075)	-0.094 (0.075)	-0.105 (0.075)	-0.091 (0.113)	-0.100 (0.075)
Separation * Initial cognitive skills parent			0.280 (0.238)				-0.223 (0.314)	
Separation unknown * Initial cognitive skills parent			0.214 (0.144)				-0.003 (0.139)	
Educational attainment parent (Low=ref.)								
Medium	-0.058 (0.135)	-0.082 (0.136)	-0.077 (0.136)	-0.147 (0.175)	-0.058 (0.135)	-0.079 (0.136)	-0.081 (0.136)	-0.053 (0.216)
High	-0.257 (0.184)	-0.339 * (0.185)	-0.334 * (0.185)	-0.394 * (0.232)	-0.257 (0.184)	-0.354 * (0.186)	-0.356 * (0.186)	-0.043 (0.273)
Separation*Medium-educated parent				0.006 (0.468)				1.371 * (0.797)
Separation*High-educated parent				-0.246 (0.586)				0.931 (0.918)
Separation unknown*Medium-educated parent				0.194 (0.290)				-0.166 (0.276)
Separation unknown*High-educated parent				0.232 (0.355)				-0.614 * (0.338)

Higher education other parent (Other=ref.)	-0.340 (0.161)	**	-0.360 (0.161)	**	-0.364 (0.161)	**	-0.359 (0.161)	**	-0.340 (0.161)	**	-0.405 (0.162)	**	-0.404 (0.162)	**	-0.391 (0.162)	**
Household income at age 12-14	-0.225 (0.053)	***	-0.081 (0.059)	***	-0.081 (0.059)	***	-0.080 (0.059)	***	-0.225 (0.053)	***	-0.127 (0.055)	**	-0.128 (0.055)	**	-0.125 (0.0554)	**
Initial cognitive skills child	-0.631 (0.061)	***	-0.624 (0.062)	***	-0.623 (0.062)	***	-0.624 (0.062)	***	-0.631 (0.061)	***	-0.663 (0.061)	***	-0.662 (0.062)	***	-0.66 (0.062)	***
Female (Male=ref.)	-0.335 (0.112)	***	-0.347 (0.112)	***	-0.346 (0.112)	***	-0.348 (0.112)	***	-0.335 (0.112)	***	-0.404 (0.113)	***	-0.403 (0.113)	***	-0.405 (0.113)	***
Migrant (Native=ref.)	0.670 (0.191)	***	0.583 (0.193)	***	0.580 (0.193)	***	0.585 (0.193)	***	0.67 (0.191)	***	0.609 (0.193)	***	0.611 (0.193)	***	0.598 (0.193)	***
Constant	-3.522 (0.134)	***	-3.714 (0.140)	***	-3.733 (0.141)	***	-3.660 (0.158)	***	-3.520 (0.134)	***	-3.854 (0.148)	***	-3.850 (0.149)	***	-3.926 (0.189)	***
<i>N</i>	13,692		13,692		13,692		13,692		13,692		13,692		13,692		13,692	

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses

Table D17 - Logistic regression estimates on the relationship an income drop of at least 25% and early school-leaving (age 15-17 and 19-21) – controlled for other shocks

	15-17		19-21	
	Mo	Mr	Mo	Mr
Income drop of at least 25% (No=ref.)		0.756 *** (0.171)		-0.274 (0.169)
On benefits (No=ref.)				
Yes		0.400 *** (0.108)		0.493 *** (0.128)
Missing		1.093 *** (0.135)		1.088 *** (0.147)
Separation (No=ref.)				
Yes		0.266 (0.177)		0.690 *** (0.223)
Unknown		0.430 *** (0.111)		0.479 *** (0.119)
Initial cognitive skills parent	-0.020 (0.057)	-0.038 (0.057)	-0.096 (0.070)	-0.123 * (0.070)
Educational attainment parent (Low=ref.)				
Medium	-0.249 ** (0.103)	-0.216 ** (0.104)	-0.293 ** (0.119)	-0.263 ** (0.121)
High	-0.303 ** (0.137)	-0.283 ** (0.139)	-0.575 *** (0.174)	-0.543 *** (0.177)
Higher education other parent (Other=ref.)	-0.395 *** (0.122)	-0.312 ** (0.124)	-0.462 *** (0.163)	-0.357 ** (0.166)
Household income at age 12-14	-0.168 *** (0.042)	-0.061 (0.048)	-0.120 ** (0.052)	-0.045 (0.055)
Initial cognitive skills child	-0.628 *** (0.047)	-0.621 *** (0.047)	-0.68 *** (0.057)	-0.689 *** (0.057)
Female (Male=ref.)	-0.39 *** (0.086)	-0.409 *** (0.086)	-0.304 *** (0.103)	-0.356 *** (0.105)
Migrant (Native=ref.)	0.389 ** (0.158)	0.321 ** (0.159)	0.439 ** (0.194)	0.343 * (0.197)
Constant	-3.259 *** (0.100)	-3.601 *** (0.108)	-3.32 *** (0.117)	-3.767 *** (0.134)
N	21,820	21,820	15,821	15,821

Note: ***p<0.01, ** p<0.05, *p<0.1; Standard errors in parentheses

ABOUT THE AUTHOR



Lynn van Vugt was born on November 8th, 1991 in Veghel, the Netherlands. She completed her Bachelor's degree in Sociology at the Radboud University Nijmegen in 2014. During her Bachelor she completed the disciplinary honours program and went for her minor to the University of Western Australia, Australia. In 2016, she completed the International Double-degree Master Sociology and Population Studies (Cum Laude). This included the Research Master Sociology and Demography (Universitat Pompeu

Fabra, Spain) and the Master of Science in Sociology (Tilburg University). She further extended her Master's degree by doing an internship at the Dutch Inspectorate of Education.

In September 2016, Lynn joined the Research Centre for Education and Labour Market (ROA) at Maastricht University as a junior researcher and one year later she started her PhD project, entitled: "Different NEETs, different needs? Explaining why vulnerable young people are more likely to become NEET". She obtained an InGRID2-grant, and visited the Swedish Institute for Social Research (SOFI) at Stockholm University, Sweden. She also presented her research at several conferences, including the Research Committee 28 on Social Stratification and Mobility (RC28), the European Consortium for Sociological Research (ECSR) and the European Network for Social Policy Analysis (ESPAnet). In 2019, she co-organized the 27th annual workshop Transitions in Youth (TIY) in Maastricht. Next to working on her PhD project, Lynn remained involved as a researcher for the Nationaal Cohortonderzoek Onderwijs (NCO).

Lynn will now continue her work at ROA as a research leader. She will be involved in several research projects, such as the National Cohortonderzoek Onderwijs (NCO) and the Onderwijs Monitor Limburg (OML).

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