NEET in the Netherlands

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Contents

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Alexander Dicks Berlin, 2023

English summary

This dissertation provides a detailed look at problematic school-to-work transitions in the Netherlands. Problematic because after education, some young people do not make the transition to work and instead become NEET (Not in Employment, Education, or Training), sometimes for years. I propose a dynamic conceptualization of NEET which understands NEET not as a state or a group but as a trajectory. Using a combination of survey and register data, paired with innovative methods, I test different mechanisms to explain these disrupted school-to-work transitions and explore who becomes NEET in the Netherlands.

In **Chapter 2** I lay out the Dutch policy context and explore how young people move from school to work. I show that about half become NEET at least once and out of those, about 18% follow long-term and therefore problematic NEET trajectories. I also show that becoming long-term NEET in the Netherlands is at least partly a social class issue and that following these problematic trajectories lead to lower incomes at age 30. In **Chapter 3** I study how social class, human capital, personality, and aspirations are jointly related to unsuccessful school-to-work transitions. It shows that multiple risk factors are at play, an important one being early school leaving. While there is no evidence for a strong role of aspirations, it shows that young people with resilient personalities have a lower probability to become long-term NEET. **Chapter 4** investigates whether some vocational education programs lead to easier-to-automate occupations than others and investigates if such automation risks can be linked to differences in the early career of graduates from vocational education. Furthermore, it investigates whether social class, cognitive skills, or personality can alleviate the possible negative relationship of automation risk and early career success. It shows that automation risk is not associated with the early career trajectory, or

NEET risks. However, the findings do suggest that graduates from easier-to-automate VET programs have lower starting wages. In **Chapter 5** I investigate how family networks and their availability to supply informal childcare as well as formal childcare availability can explain the labor market and education participation of young mothers. In line with previous research, it shows that young mothers with more of their child's grandparents living nearby are less likely to become NEET and more likely to exit NEET.

Overall, this dissertation shows that those young people who do become NEET for a long time are especially negatively selected and as such often are subjected to multiple risk factors at once. In the **Impact paragraph**, I will present some considerations for policies and possible interventions.

Chapter 1

Introduction

1.1 Motivation

When young people leave school and decide which occupation to pursue, they "construct their own life course through the choices and actions they take within the opportunities and constraints of history and social circumstances" (Elder et al., 2003, p. 11). Yet, some are more successful than others. Not having a smooth school-to-work transition or becoming unemployed at this stage in the life course may have negative consequences for later life outcomes, including wage scars, lower re-employment rates, and lower well-being (Bäckman & Nilsson, 2016; Bell & Blanchflower, 2011; Bynner & Parsons, 2002; Cockx & Picchio, 2013; Dorsett & Lucchino, 2018; Gregg & Tominey, 2005; Layte et al., 2000; Luijkx & Wolbers, 2009; Mroz & Savage, 2006; Oreopoulos, 2007; Ralston et al., 2021; Steijn et al., 2006).

In the aftermath of the Great Recession in 2008, the increased labor market inactivity and educational non-participation of youth and young adults became a great concern for European policymakers (Cuzzocrea, 2014; Eurofound, 2012, 2016, 2017). For reasons described below, they adopted the term NEET–**N**ot in **E**mployment, **E**ducation, or **T**raining–"as a key statistical indicator for youth unemployment and social situation of young people [...] alongside the youth unemployment rate and the unemployment ratio" (Eurofound, 2012, p. 21). Around the time of the Great Recession, NEET rates in several European countries went up and stayed relatively high overall. However, in the Netherlands, which is the country of interest in this thesis, the NEET rate barely changed and remained on a relatively low level (see Figure 1.1).

At first glance, low NEET rates might be considered not problematic and suggest that NEET is a non-issue in the Netherlands. However, also

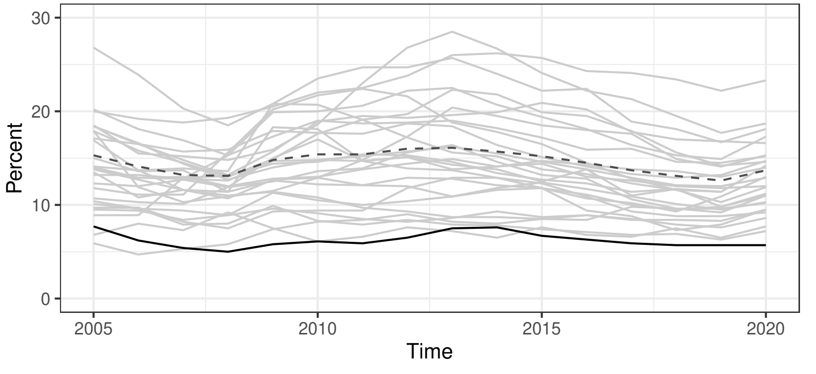


Figure 1.1: NEET (Ages 15-24) rates in EU countries (gray), EU-27 average (dotted), and the Netherlands (black) from 2005 until 2020. Source: Eurostat (2021)

low NEET rates can be problematic. First, the smaller the group is, the more negatively selected people in this group might be, and the more stigma might be attached to belonging to this group (cf. Gesthuizen et al., 2011). Hence, for individuals, being NEET might be even more problematic in a society with low NEET rates (e.g., Heggebø & Elstad, 2018). Second, the extent to which low or high NEET rates are problematic, also depends on different features of the labor market. If there is little fluctuation on the labor market and NEET episodes are long, even low NEET rates might be a societal problem (Ryan, 2001). If, however, fluctuation is high and NEET episodes short, high NEET rates can be less problematic than they seem (Ryan, 2001).[1] That is, becoming NEET might not be problematic if it is as easy to become NEET as it is to exit it. In such cases, NEET might also be a phase of orientation and role exploration (e.g., Bynner, 2007). To understand better whether becoming NEET is problematic or not, we need to take a holistic perspective of the school-to-work transition and analyze longitudinal data. In the next sections, I will lay out the plan to conduct such research. First, I will review the previous literature on NEET, after which I will reflect on the concept of NEET itself. Lastly, I will discuss the data and methods used in this thesis and give a brief overview of the following chapters.

[1]Although Ryan (2001) does not mention NEET, the argument still applies.

1.2 Previous literature on NEET

The low NEET rate in the Netherlands might be an explanation for the little attention the topic has received in public discourse or in research. To understand the placement of this thesis in the current international literature, I will show some key facts on the current state of NEET research using bibliographic data from Lens.org. Since 1990, 422 articles that included the terms "NEET" or "Not in Employment, Education, or Training" were published in indexed journals. Out of these, Figure 1.2 displays the citation network of articles with at least one citation from within this network. [2] Node size represents number of citations. Node colors represent cluster membership. The **red** cluster is the largest and most central. It includes the three most cited articles discussed below and just like these three, most studies are case studies of the UK. The **yellow** cluster includes articles from psychology on the special case of Japanese NEET. The **purple** cluster includes articles about the special case of rural NEETs. The **blue** cluster includes mainly studies from Southern Europe. Finally, the **green** cluster incldes studies about the psychiatry and mental health of NEETs.

I will briefly discuss the three most cited articles and the key takeaways from them for this thesis.

Bynner & Parsons (2002) is the central publication in this literature because it placed the NEET concept in the life course and transition-to-adulthood frameworks, recognized gender differences, and introduced psychological explanations. Using British panel data, the authors defined NEET as "6 months or more during the ages 16–18 outside education, employment, or training." (Bynner & Parsons, 2002, p. 297). They then identified factors associated with being NEET at age 16-18, of which the most important were the highest schooling qualification which partly mediates different social class indicators. In a second step, they predicted being NEET at age 21 and found the most important predictor for it was the NEET state at age 16. My thesis builds on this work by placing its analysis in an overarching life course framework. Furthermore, **Chapter 3** and **Chapter 4** build on Bynner & Parsons (2002) by considering social psychological explanations and investigating the mediating role of education and social class backgrounds. **Chapter 5** builds on the discussed gender differences by investigating the situation of young mothers.

Furlong (2006) criticized the NEET term as misleading because of its implied voluntarism. His suggestion was to either have a set of small-scale definitions, or an even broader one. The lack of an agreed definition of NEET

[2] Visualized using VOSViewer (van Eck & Waltman, 2010).

makes comparisons between countries and research using different definitions difficult, and thereby impedes the accountability of policymakers. NEET should be disaggregated for researchers to understand it and for policymakers to target it. This thesis builds on this by distinguishing different trajectories of NEET and longitudinally disaggregating these into subgroups.

Yates & Payne (2006) offered another prominent critique of the NEET term. In it, the authors presented a series of interviews with young people who were "facing substantial problems and needing intensive support" (Yates & Payne, 2006, p. 332), and "who were considered 'at risk' of not participating effectively in education or training" (Yates & Payne, 2006, p. 332). They concluded that NEET is a problematic concept because it labels young people for something they are *not* and that it mixes different people with different issues in the same group. For some, NEET might be a deliberate choice, while for others, NEET might be the consequence of an underlying issue. A focus on NEET might "risk diverting attention away from the range of other, often quite profound, risks and difficulties that they face" (Yates & Payne, 2006, p. 342). This thesis partly addresses their criticism by defining NEET not as a state but as a trajectory. Hence, the thesis does not risk mislabeling transitory NEET states as problematic.

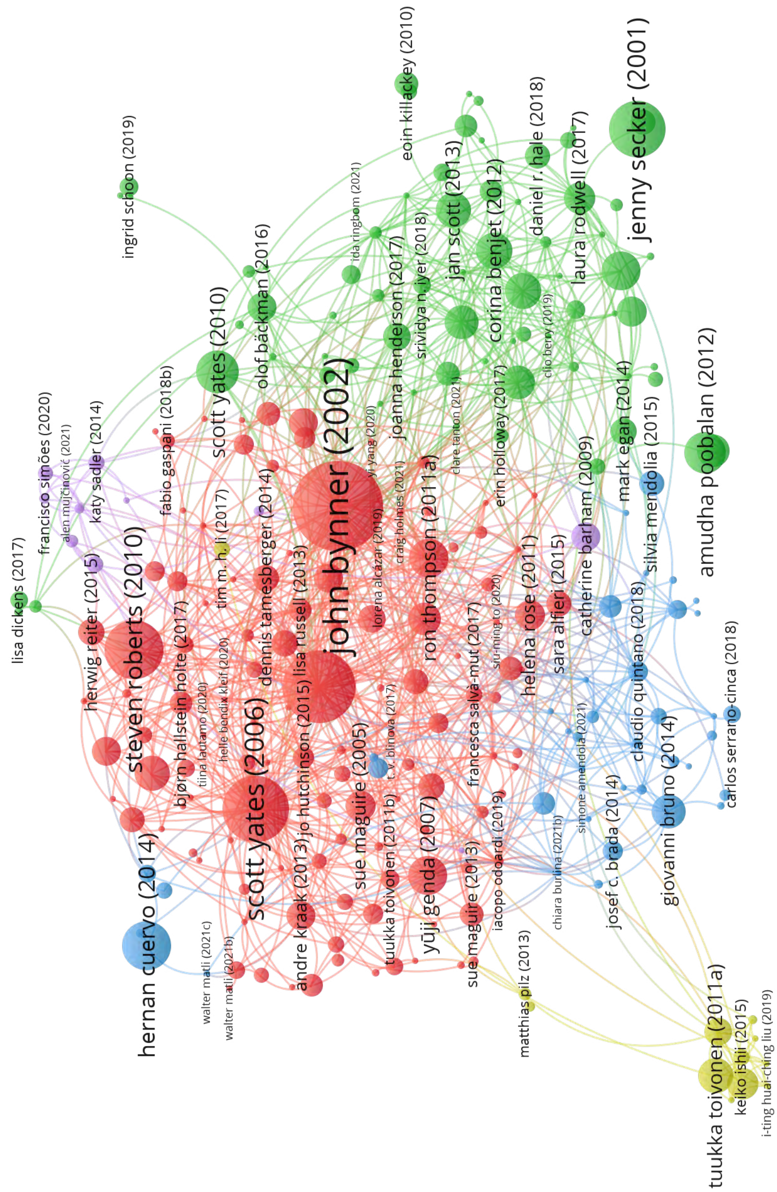


Figure 1.2: Citation network of NEET publications. Source: Lens.org

1.3 NEET and its conceptual criticism

Much of the criticism of NEET was already mentioned by the three seminal articles discussed above. However, it is worth to further discuss the advantages and disadvantages of the concept and its definition. The youth unemployment rate has long been–and still is–used to describe inefficiencies on the labor market. Yet, the definition of 'unemployment' does not capture the whole picture of young people and their economic activity. First, it only refers to those who are *actively looking* for employment and are *immediately available* for employment. Second, the *denominator*, which is the labor force, is ill-chosen. At a young age, the proportion of young people who belong to the labor force is very small because most young people are still in education and therefore not part of the labor force. Third, because many young people never had substantial employment before, they would not be eligible for unemployment insurance and thus have few *incentives to register* as unemployed. They are therefore not considered as part of the labor force either.

Originally, the NEET concept was coined in the United Kingdom in the 1990s after policy changes resulted in the abolishment of youth unemployment benefits in 1988 (Furlong, 2006). In essence, this policy changed the just mentioned incentives to register as unemployed. While NEET thus solved the problems of using the youth unemployment rate, it comes with other issues. In fact, the concept did little to clarify the problems of youth non-participation in work and education as it did to hide the different experiences and reasons for young people to become and stay NEET (Cuzzocrea, 2014; Dicks & Levels, 2018; Furlong, 2006; Maguire, 2015; Yates & Payne, 2006). Meaning, by lumping together the unemployed, the inactive, school dropouts, and other marginalized groups, it lost theoretical sharpness. Indeed, the concept was criticized for being both too broad and too narrow at the same time (Cuzzocrea, 2014; Furlong, 2006). For example, while it brought "young mothers and those with disabilities into the frame rather than further marginalizing them by use of the traditional label 'inactive' " (Furlong, 2006, p. 554) it was criticized for mixing "those with little control over their situation with those exercising choice" (Furlong, 2006, p. 554). This lack of conceptual clarity has hampered our understanding of young people who become NEET and led us to the proposition that "NEET is a bad indicator of vulnerability" (Dicks & Levels, 2018).

1.4 From a static to a dynamic view

NEET as a concept has also been criticized for its static perspective (Cuzzocrea, 2014; Furlong, 2006; S. Roberts, 2011). This is a problem that mostly stems from the use of cross-sectional data. With cross-sectional data it is impossible to tell *how* and *when* young people become NEET, and if they do, how *long* they stay NEET, and what their pathways out of NEET are. Meaning, it is also difficult to speak judgment on whether *being NEET* is problematic for young people's careers and later lives. It might well be the case that NEET is a transitory state without larger scarring effects on later life. Hence, the questions that should be asked is not "NEET or not?" but "How long?" and "When?". These can only be answered with longitudinal data. Unfortunately, to date, only few studies have used longitudinal data to study NEET and to conceptualize it as a dynamic process (see also Contini et al., 2019).

I argue in this thesis that the key for research to move forward is to conceive of NEET as a state during the school-to-work transition. For some, NEET might lead into long-term disengagement. For others, NEET might be a phase of exploration after which they continue with their transition from school to work. This comes with the need to use high-quality longitudinal data and most importantly, the appropriate methods and theories.

1.5 A short primer on sequence analysis[3]

One way of conceptualising the life-course is by assuming people move between a number of discrete states. For example, during the school-to-work transition, young people go from being in school to vocational training or university, to being employed. These moves create an individual sequential pattern of economic activity over time which-at first glance-is as unique as one's fingerprint. As sociologists, however, we tend to believe that there are patterns and regularities in the way people behave and that these regularities are shaped by the society people live in. In particular, of the restrictions and opportunities society exerts on its member's life courses via laws, norms, values, and institutions (Elder et al., 2003). More importantly, sociologists are interested in explaining such regularities (Goldthorpe, 2007). However, to explain regularities we first have to *establish the phenomenon* (Merton, 1987). Meaning, we have to recognize (and make sure) that our "explanatory

[3] For a more extensive discussion of sequence analysis see Aisenbrey & Fasang (2010), Brzinsky-Fay & Kohler (2010), and Cornwell (2015).

concerns are in fact with regularities rather than singularities, such as, say, individual lives or unique historical events." (Goldthorpe, 2007, p. 207).

Hence, the interest when dealing with sequence data lies in first describing and then explaining social regularities. This is done by comparing sequences to each other to determine their (dis-)similarity. To do so, we use algorithms such as optimal matching (OM). Originally a tool for DNA analysis in biology, it was popularized in sociology starting with Andrew Abbott's analysis of ritual dances (Abbott & Forrest, 1986). OM compares pairs of sequences and calculates a measure of dissimilarity for each pair, representing the number of changes that would need to be made in order for two sequences to be equal. Doing this for all sequences in the data yields a dissimilarity matrix which a clustering algorithm uses to sort similar observations into groups. With that, we can "detect[..] structure in a seemingly chaotic mass of information" (Brzinsky-Fay, 2014, p. 214). These clusters can be interpreted as typologies of life course trajectories and are in fact social regularities formed by aggregating and organizing singular lives. This thesis uses sequence analysis and clustering methods in **Chapter 2**, **3**, and **4**.

1.6 Data

Few young people in the Netherlands become NEET. This does not only reduce public attention and scientific interest, it also affects data availability, making it difficult to observe. That is especially the case in the usual data sources like the labor force survey and other survey data (cf. Bäckman & Nilsson, 2016). Selective unit non-response is an issue for surveys (Bethlehem & Bakker, 2014) and the lower response rate to surveys among disadvantaged groups is well-known (see Olson & Witt, 2011). Depending on the type of survey, additional issues arise when collecting life course data (see Solga, 2001). While for retrospective data collection, recall bias is an issue–people simply have problems remembering events, especially less favorable ones such as unemployment (Dex & McCulloch, 1998; Jacobs, 2002; Manzoni et al., 2010)–in prospective surveys, selective panel attrition is an important source of bias (Lavrakas, 2008; Olson & Witt, 2011). Hence, to study NEET in the Netherlands, we cannot rely on survey data alone. Therefore, in this thesis I will use the population-wide register data from the Social Statistical Database (SSB) of Statistics Netherlands (CBS) (Bakker et al., 2014). Register data are preferred to survey data when studying small and hard to reach groups because they cover the whole population. However, they come with their own shortcomings, most obviously the lack of "softer" metrics such as personality or aspirations. To alleviate these shortcomings,

Chapter 3 and **4** use matched survey data from the VOCL'99 (Kuyper et al., 2003) which do include such measures.

1.7 Aim of the thesis, outline, and main results

The aim of this thesis is to advance our understanding of NEET and to study the reasons why and when young people become, stay, or stop being NEET. The thesis consists of the following chapters:

Chapter 2 is a descriptive chapter. It lays out the Dutch policy context and explores how young people move from school to work and explores different reasons why young people become NEET in a two-step process. First, we show that about half of the sample is NEET at least once. Out of those, we consider about 18% to be long-term and therefore problematic NEET trajectories. Furthermore, we show that NEET in the Netherlands is at least partly a social class issue, as those with unemployed fathers and those living in rental houses are more likely to become NEET. Lastly, this chapter also estimates that those who follow these problematic trajectories earn much lower incomes at age 30 than their peers who followed more standard school-to-work trajectories.

Chapter 3 builds on **Chapter 2** and adds a unique combination of survey and register data to study how social class, human capital, personality, and aspirations are related to unsuccessful school-to-work transitions. It answers the research question, *to what extent and how do human capital, social class, personality, and aspirations predict a school-to-work trajectory that is predominantly characterized by time spent in NEET?* We find that multiple risk factors are at play, an important one being early school-leaving. Unlike previous research, we do not find strong evidence for the role of aspirations, however we do find some evidence that young people with resilient personalities have a lower probability to become long-term NEET.

Chapter 4 uses an innovative framing of automation risks as a property of vocational education programs to answer whether such automation risks are already responsible for changes in the school-to-work transition and the early career of graduates from vocational education. Furthermore, we investigate whether social class, cognitive skills, or personality can alleviate the possible negative relationship of automation risk and early career success. It answers the research question, *to what extent automation risks affect the early career paths and wage development of VET graduates during the school-to-work transition and to what extent cognitive skills, personality traits, and* *social class mitigate these possible differences in labor market outcomes because of automation risks?* Using sequence analysis, we find four post-VET trajectories that describe different pathways of Dutch VET graduates. However, automation risk is not associated with following either of the four trajectories. Using growth-curve modelling, we found lower starting wages, but not lower wage growth, for easier-to-automate VET programs. Apparently, automation does not (yet) force young people out of the labor market, but it does seem to depress wages.

Chapter 5 investigates how family networks and their availability to supply informal childcare can explain the labor market and education participation of young mothers and how that interacts with formal childcare. It answers the research question, *to what extent the characteristics of young mothers, their parents, partners, and the institutional context can explain why some young mothers a) become NEET or b) exit NEET status?* Using Dutch register data, we link young mothers to their children, their parents, and their partners. We then use spatial distance as a proxy measure for availability of informal childcare. In line with previous research, we find that young mothers with more of their child's grandparents living nearby are less likely to become and more likely to exit NEET.

Chapter 6 offers a conclusion and summary of the main results of the thesis and provides an outlook for future research and reflects on the policy implications of the findings. It also offers a short review and suggestions for interventions.

Chapter **2**

Exploring NEET Trajectories in the Dutch context[1]

2.1 Introduction

As laid out in **Chapter 1**, the Netherlands is a particularly interesting case to study youth that are not in employment, education, or training. The Netherlands consistently has one of the lowest NEET rates in the European Union. Still, the Dutch NEET case is notoriously understudied. We know especially little about how and which young people in the Netherlands become NEET. Therefore, in this chapter, we will explore how Dutch youth leave school, how and when they find work, and if not how long they stay NEET. To do that, we describe typical school-to-work transitions using sequence analyses.

Prior, to this explorative exercise, the chapter will also discuss the Dutch policy frame in which these young people navigate their school-to-work transition. We argue that the low NEET rate may at least partly be attributable to the education system, labor market regime, welfare arrangements, and family policies. To understand why, it is crucial to understand how the Dutch institutional context works. To lay the groundwork for further anal-

[1]This chapter was joint work with Mark Levels and written as one of the main products of the international research project *Understanding NEETs*. It is published in Levels, Mark, Christian Brzinsky-Fay, Hirofumi Taki, Janina Jongbloed, and Craig Holmes (2022). *The Dynamics of Marginalised Youth. Not in Education, Employment, or Training Around the World.* London: Routledge. In it, colleagues from Germany, the UK, France, and Japan describe the situation of NEET youth in their respective countries using a common framework of policy analysis, theory, longitudinal data, and sequence analysis. We would like to thank our colleagues of the project who all gave valuable comments on the manuscript at different stages.

ysis, this chapter will first present the macroeconomic and policy context of the Netherlands. On this basis, we will then explore young people's school-to-work trajectories with a focus on describing those trajectories which are characterized by considerable time spent in NEET.

2.1.1 The economic context

Figure 2.1 shows the most relevant labor market indicators over the last two decades. Immediately apparent are the massive changes in GDP during the Great Recession in 2008/2009 and the COVID-19 pandemic in 2020. The unemployment rate went up after each crisis and the youth unemployment rate largely follows the general unemployment rate, albeit more extremely. Youth unemployment rates are often more volatile, especially during economic slumps (Borghans & Wolbers, 2003). Furthermore, we see that the youth unemployment rate is much higher than the NEET rate. This is due to the differences in denominators. While the denominator of the youth unemployment rate is the workforce, the denominator of the NEET rate is the population. The NEET rate can also be split up into active and inactive. Active corresponds to the youth unemployment rate while inactive is the rate of youth out of the labor market and out of education. By splitting the NEET rate, we see two things. First, that there are more inactive than active NEET. Second, that the inactive NEET rate is less volatile than the active NEET rate. This makes sense because "active NEETs" are looking for employment, and as such are more likely to respond to the economic cycle. However, this also means that "inactive NEETs" might be something to worry about. If the economic cycle is not relevant for them, then what is? Clearly, other factors are at play.

2.1.2 The education system

As Figure 2.2 illustrates, the system is highly tracked. Tracking is determined by the pupil's score on a national test in math and language and the primary school teacher's advice, in group 8 (around age 12) of primary education. Admission to post-secondary and tertiary education programs is conditional on obtaining credentials from relevant secondary education programs. To obtain such diploma, pupils' abilities are tested with centralized exams. This standardization of output is meant to ensure that Dutch school-leavers at least have gained the minimum requirements to succeed in post-secondary or tertiary education.

After primary education, children can generally attend one of three secondary pre-vocational tracks, or one of two general academic tracks.

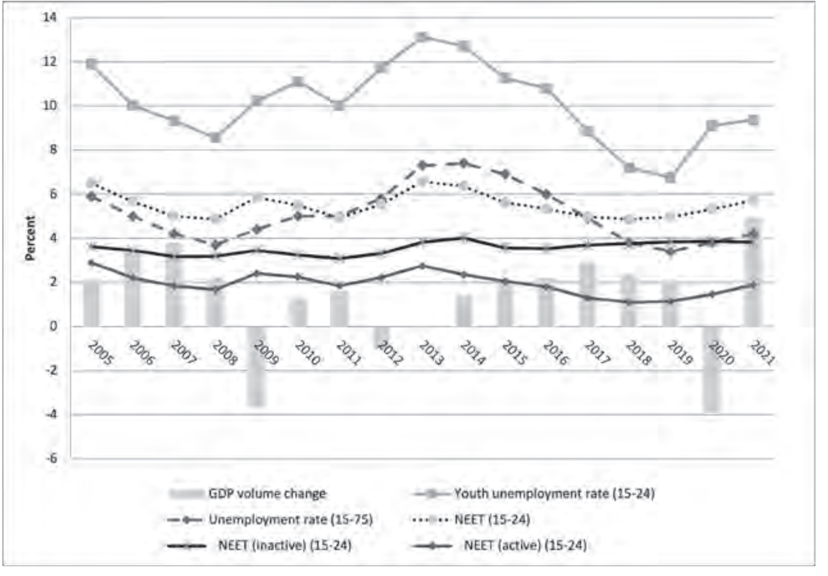


Figure 2.1: Trends in unemployment and NEETs in the Netherlands. Source: CBS StatLine, own calculations.

The three secondary pre-vocational tracks (VMBO) prepare for vocational training at the upper-secondary level (MBO, four levels). In MBO education a distinction is made between programs that are primarily school-based (BOL, less than 60% workplace training) and programs that are primarily workplace-based (BBL, at least 60% workplace training). In the last years, the highest level has been steadily growing in attendance. While in 2013, 44% of MBO students were enrolled in level 4, in 2020 57% were enrolled in MBO level 4 (Statistics Netherlands, 2021a, own calculations). The academic tracks in secondary education (HAVO, VWO) prepare for universities of applied science (HBO) and research universities (WO) respectively. A diploma at MBO level 4 also qualifies for HBO. Special education and practical education tracks are designed for schooling children with special needs or learning disabilities, respectively. Generally, mobility between tracks is possible. In 2020, around 8% of VMBO students moved up to HAVO, 3% moved down from HAVO to VMBO, 5% moved up from HAVO to VWO, and 6% moved down from VWO to HAVO (Statistics Netherlands, 2021a, own calculations). However, lately, the rate of those who move up the next track after graduation in one track is decreasing (CPB, 2022). The rate of mobility also depends on whether a particular school offers multiple tracks (see CPB, 2022). And lastly, while track mobility is theorectically available to everybody, in reality it is used differently by pupils of different socioeconomic backgrounds. For example, it is more often used by pupils from higher socioeconomic backgrounds (CPB, 2022; Jacob & Tieben, 2009) but also more often by pupils with an immigration background (CPB, 2022).

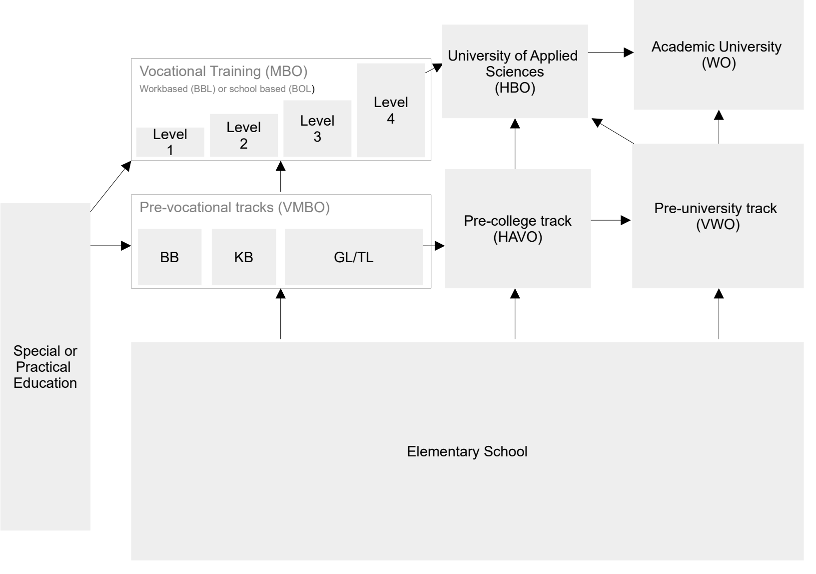


Figure 2.2: Schematic overview of the Dutch education system.

The Dutch education system is thought to limit the NEET rate in various ways. For one, primary and secondary education are offered free of charge. Dutch pupils between 16 and 18 are also obligated to obtain a starting qualification. A starting qualification is a diploma that is equivalent to MBO level 2, HAVO, or VWO (equivalent to ISCED Level 3C short or 3A). Pupils who, against this obligation, leave the education system before the age of 18 and without such a diploma are considered early school-leavers. Pupils between 18 and 23 who do not have a starting qualification receive government support of a regional coordinator. Generally, the system is designed to keep pupils in school until they have a starting qualification. Second, the costs of education are low. In general, people who are registered for full-time or dual programs in secondary education, school-based programs in the MBO, or in tertiary education are eligible for financial support in the form of a monthly payment and free travel with public transport. The amount depends on the income of parents. Youth in secondary education and MBO have to be at least 18 years old to be eligible for financial support while for youth in tertiary education there is no minimum age requirement. Eligible are those who are enrolled in an education program that is accredited and takes longer than one year. Eligibility ends at age 30.

Vocational education

The pre-vocational track is the most common form of education in the Netherlands. Over half of all pupils in secondary education follow VMBO (Inspectorate of Education, 2020), and about 40% of all working Dutch adults have been educated in MBO (Karsten, 2016). Hence, it is worth to focus on the Dutch VET system as one of the key reasons for the low NEET rate. As can be seen in Figure 2.2, the vocational tracks in the Netherlands are quite intricate. In secondary education, VET has three tracks (the GL and TL track are very similar and therefore shown as one). The track considered lowest is VMBO-BB ("basisberoepsgerichte leerweg"), which teaches students the basic skills of a craft. It is the least academically challenging track in secondary education and has a light central exam. Apart from the vocational courses, it offers general courses at a basic level (e.g., Dutch, English, Math). The second track is the VMBO-KB (or: "kaderberoepsgerichte leerweg"), in which students take a more advanced training for a specific sector. The VMBO-GL ("gemengde leerweg") track offers general courses at a higher level, but also offers a modest amount of practical education. As only few students take this track, it is often combined with the only general track in VMBO, VMBO-TL ("theoretische leerweg"). This track offers general education with specialization areas (e.g., in math/science or economics) and is an entry ticket into the highest MBO track (4) and the HAVO track.

In upper secondary vocational education, MBO is organized in four tracks. The lowest track (MBO level 1) is an entry level program accessible for students who do not have a diploma from secondary education (or have practical education). Its diploma is not considered a *starting qualification* for the labor market, but a steppingstone for programs at level 2 (basic vocational education). MBO level 2 is typically aimed at students who had a VMBO-BB or VMBO-KB qualification. MBO level 3 programs are professional training programs, that prepare for independent craftmanship in professions in various sectors and is typically aimed at students who had a VMBO-KB qualification. The highest track (MBO 4) prepares for middle management functions or functions as specialists but is also an entry ticket to the HBO. It is typically aimed at students who had a VMBO-GL/TL qualification. The HBO ("hoger beroepsonderwijs") is in essence a form of tertiary vocational education at ISCED level 5.

Programs in the MBO can be offered in two different learning pathways. The mostly school-based pathway (BOL) includes between 20% and 60% of practical training. The workplace-based pathway (BBL) is a dual track that offers at least 60% practical education. To ensure that programs in the Dutch VET system teach relevant occupationally specific skills, there are close institutional linkages with employers. Schools and employers work together in an organization that was founded for this specific reason (the so-called "Samenwerkingsorganisatie Beroepsonderwijs Bedrijfsleven"). One task of this organization is to establish which skills are needed for the various MBO-credentials. All MBO programs base their curricula on so-called competency-based qualification dossiers. These dossiers are national frameworks that describe for each MBO program which skills, knowledge and competences students in that program should learn, and at which level (Van der Meijden & Petit, 2014).

Compared with other European countries, Dutch VET graduates are relatively successful in making the school-to-work transition (Cedefop, 2020). The vocational education system generally succeeds well in teaching students relevant occupationally specific skills, and a vocational degree in the Netherlands is not perceived by employers as a signal of low academic performance (Muja et al., 2019). All of this ensures a relatively smooth labor market allocation for vocationally educated children.

However, the downside to this well-functioning allocation system may well be that those who fail in quickly making the successful school-to-work transition are perceived by employers as fundamentally unfit for the labor market. Early inactivity could act as a trap for Dutch school-leavers (Steijn et al., 2006; Wolbers, 2007) especially when outflow is low, and spells are long (Luijkx & Wolbers, 2009; Ryan, 2001). Government policies are often criticized for failing to meet the real needs of youth and instead focus policies "on the school-age group, leaving young people who struggle to make successful first steps into the labor market, relatively unattended" (Bekker & Klosse, 2016, p. 249).

2.1.3 The labor market

The Dutch labor market is highly institutionalized. The government actively works with unions and employer organizations to co-design labor market arrangements. About 75% of all labor contracts are the result of collective bargaining agreements, that are mostly negotiated at the industry level

(Hartog & Salverda, 2018). Such agreements include seniority wage scales for occupational groups. Also resulting from this strong collective outlook on employee-employer relations is the fact that the Dutch labor market traditionally has relatively strong employee protection (OECD, 2020). The strong position for insiders is commonly thought to worsen the position of newcomers on the labor market and to be detrimental for young people (Muffels, 2013).

Another main development on the Dutch labor market has been flexibilization. The number of flexible jobs has increased steadily from 16% in 2001 to 26% in 2016 (Hartog & Salverda, 2018). Flexible jobs include jobs with a temporary contract, such as work for a temp agency, zero-hours contracts, and probationary periods of jobs that will eventually become permanent. Temp agency work has increased about 30% between 2001 and 2016 (Hartog & Salverda, 2018). Young people are about 2.5 times more likely than the general working population to have a flexible job (see Figure 2.3). However, young flexworkers are also more likely to find permanent jobs than older flexworkers (Mattijssen & Smits, 2017).

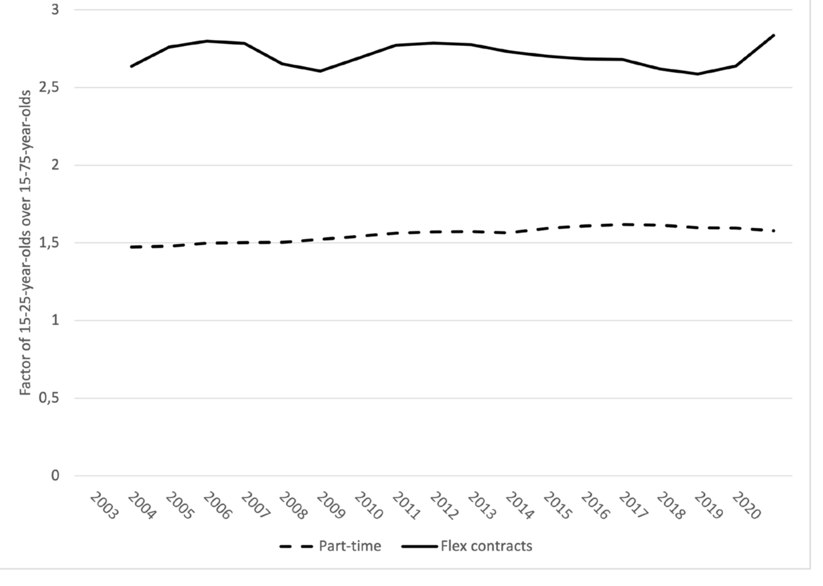


Figure 2.3: Young people in flexible and part-time contracts compared to the general population. Source: CBS StatLine, own calculations.

Young people are also about 1.5 times more likely to have part-time jobs than the general working population (see Figure 2.3). In the last two decades, the number of part-time work arrangements has risen significantly, and about half of all employment is currently part-time, meaning less than 35 hours per week (Hartog & Salverda, 2018). Among young people aged 15 to 24, the number of jobs of less than 12 hours a week rose from 36% in 2001 to 44% in 2016 while an increasing number of young people in education also have small jobs (Hartog & Salverda, 2018).

Wages are regularly renegotiated by the social partners to adjust for inflation and productivity differences in collectie bargaining schemes. The collective bargaining thus forms the prime source of income increase for Dutch workers which has not changed much between 2001 and 2016 (Hartog & Salverda, 2018). In addition, all employees in the Netherlands over 21 are entitled to the legal minimum wage. As of January 2022, the minimum wage was determined by law to be €1,725 before taxes. Young employees are entitled to the so-called youth minimum wage, which is a percentage of the minimum wage. This depends on one's age: a 16-year-old is entitled to a wage of 34.5% of the minimum wage; a 20-year-old to 80%.

The availability of flexible work arrangements paired with a minimum wage might limit the number of young people who become NEET.

2.1.4 Welfare state arrangements

Young people who become unemployed may be eligible for unemployment benefits. Employees that become fully or partly unemployed are eligible for receiving unemployment benefits ("WW-uitkering") subject to the following conditions: one must a) have been employed, not on full-time unpaid leave, and not yet retired, b) be a legal resident, c) lose at least 5 hours of employment per week and no longer receive income over these hours, d) be directly available for work, e) have worked for at least 26 weeks for an employer in the 36 weeks before unemployment, and f) not become unemployed due to one's own doing. The scheme is designed to stimulate reintegration. Eligible workers who become unemployed are entitled to at least 3 months of benefits, but the actual length of the period one is eligible for receiving unemployment benefits depends on one's work experience. The more working years one has gained, the longer one is entitled to receiving benefits. The maximum period for receiving benefits is two years. In collective bargaining agreements, additional periods (up to 38 months) may be agreed to. The actual height of the benefits depends on one's income. In the first two months of unemployment, benefits are set at 75% of the average daily wage earned in the year before unemployment. For the remaining period, benefits are 70% of the average daily wage. This is for those who become fully unemployed. To stimulate reintegration, the WW-program also supplements income for those who accept a job at a substantially lower wage than the WW-wage (87.5%). People who did not find work after their unemployment benefits end, may apply for General Welfare ("Algemene Bijstand").

In general, people over 18 are entitled to General Welfare if they do not have sufficient income or capital to pay for basic living standards and are not entitled to other benefits (such as unemployment benefits). Further conditions are that one is a legal resident of the Netherlands and is not institutionalized or in prison. To stimulate reintegration into the labor market, several additional conditions must be met. Welfare recipients must actively work on their reintegration. They a) must accept and keep any job offered to them, b) register with an employment agency, c) be willing to travel to and from work for 3 hours a day, d) willing to move to a location where one can find a job, e) do anything in one's ability to acquire relevant skills and knowledge, f) cooperate with any government support in finding employment, and g) dress, behave and groom oneself in a way that does not hamper one's ability to get a job. The government can withhold payment of benefits for up to three months for non-compliers (Rijksoverheid, 2021d). These conditions are not applicable to single parents with one or more children under 5, or for those who are permanently incapable of working. The amount of benefits depends on one's age and living situation. People of 21 years old who are married or living together are entitled to 100% of the minimum wage. Singles over 21 to 70% of the minimum wage; single parents receive an additional payment for children. For those under the age of 21, the welfare is capped at a lower amount. Young people under the age of 27 are not entitled to General Welfare if they can follow education programs that would entitle them to government study financing programs.

Besides a large share of "active NEETs", some who become NEET in the Netherlands seem to be long-term inactive. Some of these may be disabled (Eurofound, 2016) and could be entitled to benefits under the Disablement Assistance Act for Handicapped Young Persons (Wajong) and the Participation Act of 2015. Young people can get disability benefits if - before the age of 18 – they contracted an illness or disability so serious that they cannot work. Youth between 18 and 30 can be eligible for these benefits if they become seriously ill or disabled during education. In all cases, additional conditions are that these young people have not gained any work experience and cannot work, are living in the Netherlands, are older than 18 (but not retired), have not been in prison for longer than a month, and follow several rules. Evaluation of the ability to work is done regularly by the Employee Insurance Agency (UWV). Young people with a disability or illness that permits them to work, will be helped to find a job in two programs. First, in the job creation program ("banenafspraak") which is a collaboration between the government and employers, to create jobs for partly disabled youth. Young people who can work, but who cannot make the minimum wage, are also eligible for this program. Government subsidies make hiring these youths attractive to employers. Second, youth who need extra support to work, can be placed with so-called sheltered jobs ("beschut werk"), for example at social workplaces specifically designed to employ people with disabilities.

All in all, these welfare state arrangements in the Netherlands clearly are designed to work to "activate" inactive young people and to keep young people either in education or employment.

2.1.5 Family policies

Parental leave schemes are important to understand labor market participation around childbirth. Paid parental leave enables parents to temporarily stop working and take care of their children without the fear of losing their job or reducing their incomes. During pregnancy, employees are eligible to receive at least four and up to six weeks pregnancy leave before childbirth. After childbirth, maternity leave amounts to at least ten weeks and mothers continue to receive their full salary while their employers are compensated 100% by the government. If less than six weeks pregnancy leave are taken before birth, the remaining amount can be added to maternity leave for a total of 16 weeks leave (Rijksoverheid, 2021a).

For partners, the Netherlands have paternity leave. However, compared to other countries, the Netherlands had a relatively short paternity leave of two days, which also where not compensated (van Belle, 2016). Since 2019, partners are entitled to one working week of paternity leave within four weeks after birth (Rijksoverheid, 2021b).

Parental leave can be taken at any point in time for anyone with children under the age of 8. Parental leave is generally unpaid, although there might be special agreements with employers. Contrary to maternity and paternity leave, the duration doubles in case of twins and is also available for adoption. Parental leave can be at maximum 26 times the number of weekly working hours and can be taken by both parents (Rijksoverheid, 2021c).

Aside from leave schemes, childcare is an important source of support for parents. However, Dutch parents are traditionally reluctant to make use of full-time formal childcare options (Portegijs et al., 2006), possibly because formal childcare has long been looked upon as being of low quality

(Leitner, 2003). Instead, many Dutch parents rely on informal care to supplement formal childcare, most often provided by grandparents (Knijn & Liefbroer, 2006; Mills et al., 2014). Those who do use childcare tend to do so in part-time, to supplement part-time work, with attendance being much higher for shorter stays than for longer stays (Mills et al., 2014). Even though there are extensive subsidies in place, people with lower income are less likely to use childcare than those with higher income (Mills et al., 2014). The Childcare Act of 2005 intended to increase the labor participation rate of young parents (CPB, 2011). It did so by increasing subsidies for formal childcare for lower income families. The size of the subsidy is partly based on household income and parents with higher incomes receive lower subsidies. It also depends on the total costs of childcare, and on the number of children in a family. Parents are entitled to such subsidies if they are eligible and make use of childcare in a registered childcare facility or a registered host-parent. Eligible are only working couples or single working parents. Parents who do not work are eligible if they are in a reintegration track and actively try to return to the labor market, migrants in an integration course, or are in education. Note that under this law, childcare is not subsidized if at least one parent is not working or not in education (NEET). A large-scale evaluation study found that the 2005 reform indeed increased labor market participation of young mothers. However, lower educated young mothers were not positively affected (CPB, 2011). In 2012, subsidies were cut in response to the Great Recession. All in all this might have negative consequences for young mothers and might drive them to become NEET, as discussed in more detail in **Chapter 5**.

2.2 Expectations

The Dutch institutional context leads to specific expectations about the amount and composition of young people who become NEET in the Netherlands.

First, given the well-functioning transition system, we expect that in the Netherlands, most young people are NEET for a short period of time, if at all. This is also aided by the just discussed activating welfare system, available employment in various forms (part-time, flexible), and a minimum wage. Hence, most of the system is already geared towards avoiding becoming NEET. However, we see a real risk of “falling through the cracks” and expect that there exists a group with long NEET spells and difficulties of re-integrating.

Second, the strong stratification and differentiation of the Dutch education system together with job queueing and sorting by employers based on credentials results in higher long-term NEET rates for early school-leavers.

Third, socioeconomic background is not expected to play a large role in explaining who becomes NEET in the Netherlands, net of schooling. In the highly stratified Dutch system, tracking happens relatively early, which itself is associated with stronger social background effects. While there is a relationship between lower socioeconomic background and attending vocational education, given the good reputation of vocational education and the strong emphasis on skills and institutional linkages to the labor market, we expect that vocational education enables those with a lower SES background to still be relatively successful in making the school-to-work transition.

Fourth, immigrants and children of immigrants are expected to be vulnerable to become NEET. In a selective labor market, youth with immigrant backgrounds may face many disadvantages, even if their conditions of access to the labor market vary depending on their social and educational characteristics. On average, immigrant children achieve lower levels of education and are more often early school-leavers (ROA, 2016). Furthermore, ethnic discrimination is also an issue on the Dutch labor market (Thijssen et al., 2021). This would lead us to believe that immigrant youths will be more likely to become NEET, and also more likely to become NEET for longer periods of time.

Fifth, although the number of young people who become NEET and the number of those who become NEET for the long-term is expected to be relatively low in the Netherlands, young women with children may form an exception. The Dutch have a very liberal fertility control culture. About half of young women aged 16-30 use birth control pills (Statistics Netherlands, 2019) and abortion laws are very liberal, although the incidence rare (Levels et al., 2012). Dutch women become mothers relatively late. The mean age at first birth in the Netherlands was 29 in 2018, which is relatively high (Human Fertility Database, 2018). However, the traditional male breadwinner model has long been dominant in the Netherlands (Clerkx & van IJzendoorn, 1992). While this has changed partly, child-care is still regarded by many as the responsibility of women (Mills et al., 2014). As such, the Netherlands was generally regarded as an example of a conservative model of work-family reconciliation (Gornick & Meyers, 2003). In addition, welfare may be a trap into NEET status for some young women. Welfare benefits are generally not granted to Dutch youth, so welfare does not play a big role in explaining NEET in general. However, single parents are exempt from certain activating measures. Thus, we expect young women with children to become long-term NEET more likely.

2.3 Data and measurements

2.3.1 Sample selection

From the register data, we select those individuals who have left secondary education and then follow their activities in the register data for ten years. To reduce computational load issues regarding the optimal matching algorithm, we draw a random sample of 25% of the 1987 birth cohort. We chose 1987 because it allows us to observe them from age 16 until age 30. Furthermore, we only select those for whom we have at least nine out of ten years of full sequence information and who spent at least one month in NEET during the observation window. After list-wise deletion of missing values on our variables of interest, our final analytical sample consists of N = 23,342.

2.3.2 Sequence data

The analysis of the NEET patterns is done with sequence and cluster analysis using data from the Social Statistical Database (SSD) by Statistics Netherlands (CBS) (Bakker et al., 2014). We have monthly information on the employment and education activities of the entire Dutch population. We obtain the monthly activity after merging two datasets from the SSD. One includes spell data on the main economic activity based on the main source of income. The second dataset includes spell data on registrations in publicly funded education. We merge the two variables, whereas education always overwrites other states. We do this because the analysis cannot handle simultaneous states. Following the paradigm of human capital and investment in skills, we view education as the more important state of the two. We recode the original variables into (1) Working (including employee, shareholder, self-employed, other activities), (2) NEET (including recipients of unemployment insurance, recipient of welfare, recipient of other social benefits, recipient of illness and disability benefits, recipient of pension), (3) Vocational training (including (not yet) pupil/student with income, (not yet) pupil/student without income, other without income), (4) Higher Education, and lastly (5) Secondary Education and below (including primary education, practical education, secondary education). Lastly, we start our observation in 2001 and end in 2017. From every year, we exclude the month of August. We do this because in the register data, school-leaving seems to be an artefact of the school registers which end in July and start in September. Without excluding this break, we would overestimate the amount of school-leavers. We then align sequences on the first month spent out of secondary education.

2.3.3 Other variables

Gender was obtained from the SSD registers. We distinguish women (coded as 1) from men (0). Using the same data, we distinguish between native born with two native born parents (coded as 0), those born abroad with at least one foreign born parent (coded as 1), and pupils born abroad with two foreign born parents (coded as 2). Furthermore, we know the provinces in which youths lived when they were leaving school. The school leaving diploma distinguishes between those with no diploma at school-leaving (0), those with a diploma at VMBO (and MBO level 1) (1), and those with a diploma at HAVO, or VWO (and MBO level 2) (2). Socioeconomic status is measured in three ways. First, we use the activity state of the father during the year our population of interest was 16 years old. We distinguish working (and education) (0) from unemployment/welfare (1), sickness/pension (2), and not matched in registers (3). Second, we use homeownership and distinguish between youth who live in a home that is owned (0) from a rental with (1) and without (2) subsidies. We also measure the average monthly household income in the year they were 16.

2.4 Analyses and results

We analyze the data in four steps. First, we perform sequence and cluster analyses. For this we use TraMineR (Gabadinho et al., 2011). We use Ward's algorithm for clustering. Optimal matching costs are set to 1 and 2. We do this because no substantial reasons, theoretical or otherwise, would lead us to assume a different cost structure (cf. Brzinsky-Fay, 2007; Brzinsky-Fay & Solga, 2016). The clustering ensures that sequences that are most alike are clustered, and that the clusters are as distinct as possible. This produces a number of patterns that can be seen as typical and representative to typical patterns that can be discerned in the data. However, the data-driven nature of our analysis should not be over-stated. Although based on data-driven indicators, we also made theoretically guided decisions which number of clusters makes the most sense. We then describe typical patterns of sequences based on our understanding of the patterns in the data. Secondly, we explain which trajectory is followed by way of multinomial logistic regressions using Stata (StataCorp, 2019). We use the patterns as dependent variables to assess the extent to which various patterns can be explained by characteristics of individuals and their families. Thirdly, we analyze the number of NEET months after school-leaving. Fourthly, we use the patterns from the sequence analysis as independent variables to investigate the extent to which the different patterns can explain income at age 30.

2.4.1 Sample description

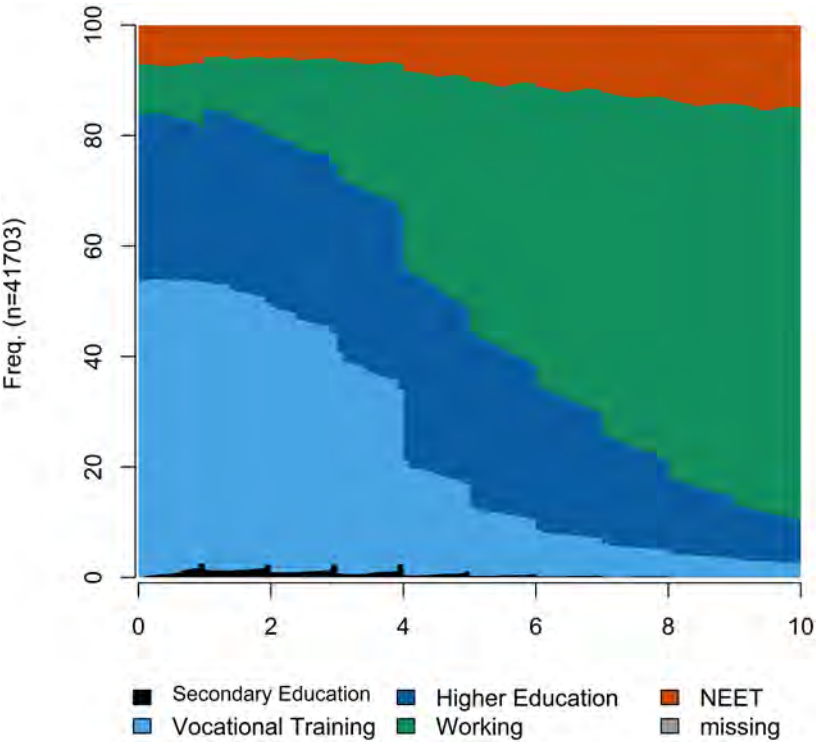


Figure 2.4: Status proportion plot for the whole sample. Source: Statistics Netherlands, own calculations.

In Figure 2.4 we present school-to-work sequences of the full sample in a state distribution plot. The graph depicts how often each status occurs in each month and illustrates how the frequencies of statuses evolve over time. After leaving school, most remain in education and continue into post-secondary or tertiary education. Others move into employment, and their proportion increases over time. We see that those with NEET status are a non-negligible minority. We also see a slight increase in NEET rates over time.

Given the institutional configuration of the Netherlands, we expected that VET trained youth would be less often NEET and less often long-term NEET, and that early school-leavers, immigrants, and women with children would be more likely long-term NEET. Table 2.1 presents the comparison of our NEET sample with youth who never become NEET during the school-to-work transition on standard demographic variables. These descriptions already provide some first clues about our expectations. First, in general, our sample with those who experience at least one month of NEET status differs on some interesting points from the overall sample. The percentage of people without a diploma after first-time school-leaving is indeed larger in the NEET sample (17% compared to 13.4% overall). Also, first generation (5.4%) and second generation (16.8%) immigrants are somewhat overrepresented in the NEET sample compared to the overall sample (where the percentages are 4.3% and 13.9%, respectively).

Next, we test parametrically whether these descriptive differences are statistically significant, and perform logistic regression analysis on the occurrence of at least one month of NEET. We estimate a multivariate model with all variables we included in the descriptive analyses, including school-leaving diploma, gender, immigration background, province, father's and mother's employment at age 16, house ownership and household income. Figure 2.5 shows the average marginal effects (AME) from the logistic regression. These analyses largely confirm the descriptive conclusions. Those without a starting qualification are much more likely to be NEET for at least one month, and compared to those who have a school-leaving diploma from HAVO or VWO, those from the VMBO have a similar likelihood to be in the NEET sample.

Both first- and second-generation immigrants are more likely to experience one month of NEET than Dutch natives. Young women more probably experience one month of NEET than men, but the differences are small. Among those who have experienced at least one month of NEET, the father is less likely to be employed and more often not matched at all in the registers. Not being matched can have many reasons, some examples might be not living in the Netherlands, not being alive, or not being registered as a parent. We could only speculate what this coefficient means above and beyond a possible "absentee father" effect. Lastly, those who were NEET were more likely to grow up in rented housing, and in households with lower incomes.

Table 2.1: Summary statistics by sample

	Never NEET		NEET = 1 month		Total	
	Freq.	%	Freq.	%	Freq.	%
Gender						
Male	9,522	51.8	11,751	50.3	21,273	51.0
Female	8,843	48.2	11,591	49.7	20,434	49.0
School leaving diploma						
No diploma	1,613	8.8	3,976	17.0	5,589	13.4
HAVO/VWO	7,017	38.2	7,591	32.5	14,608	35.0
VMBO	9,735	53.0	11,774	50.4	21,509	51.6
Immigration background						
Native	15,978	87.0	18,149	77.8	34,127	81.8
1st Generation	506	2.8	1,270	5.4	1,776	4.3
2nd Generation (one parent)	1,881	10.2	3,923	16.8	5,804	13.9
Father's employment status (Age 16)						
Working (or Education)	16,149	87.9	18,381	78.7	34,530	82.8
Unemployment/Welfare benefits	513	2.8	1,237	5.3	1,750	4.2
Sickness/Other benefits/Pension/no income	1,021	5.6	2,013	8.6	3,034	7.3
Not in registers	682	3.7	1,711	7.3	2,393	5.7
Mother's employment status (Age 16)						
Working (or Education)	12,646	68.9	14,348	61.5	26,994	64.7
Unemployment/Welfare benefits	723	3.9	2,183	9.4	2,906	7.0
Sickness/Other benefits/Pension/no income	4,737	25.8	6,388	27.4	11,125	26.7
Not in registers	259	1.4	423	1.8	682	1.6
Household home ownership (Age 16)						
Owned	13,914	75.8	14,614	62.6	28,528	68.4
Rented	2,992	16.3	4,765	20.4	7,757	18.6
Rented (subsidized)	1,459	7.9	3,962	17.0	5,421	13.0
Province						
Drenthe	570	3.1	796	3.4	1,366	3.3
Flevoland	455	2.5	666	2.9	1,121	2.7
Friesland	769	4.2	985	4.2	1,754	4.2
Gelderland	2,504	13.6	2,710	11.6	5,214	12.5
Groningen	546	3.0	840	3.6	1,386	3.3
Limburg	1,217	6.6	1,596	6.8	2,813	6.7
Noord-Brabant	2,863	15.6	3,401	14.6	6,264	15.0
Noord-Holland	2,408	13.1	3,631	15.6	6,039	14.5
Overijssel	1,464	8.0	1,607	6.9	3,071	7.4
Utrecht	1,310	7.1	1,672	7.2	2,982	7.1
Zeeland	490	2.7	504	2.2	994	2.4
Zuid-Holland	3,769	20.5	4,934	21.1	8,703	20.9
Household income (Age 16), Mean (SD)	41878.91	(20775.49)	38753.49	(22127.25)	40129.75	(21598.01)
Total	18,365		23,342		41,707	

Source: Statistics Netherlands, own calculations.

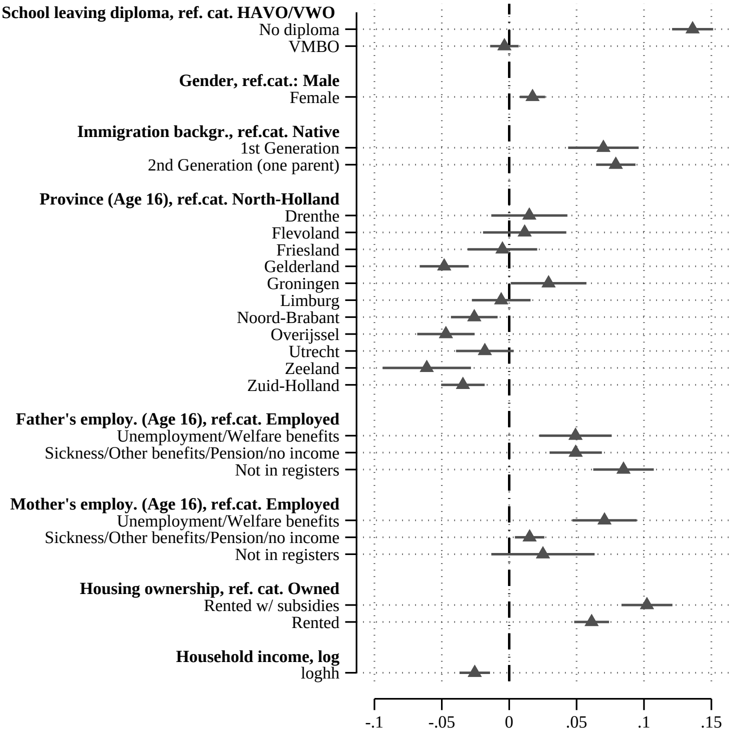


Figure 2.5: Logistic regression of NEET sample selection (Never-NEET vs NEET for at least one month), Average Marginal Effects. Source: Statistics Netherlands, own calculations.

2.4.2 Sequence analysis: the patterns of NEET in the Netherlands

The goal of the sequence analyses is to explore whether we can observe meaningful regularities in patterns related to NEET status during the school-to-work transition. We analyze young people who experience at least 1 month of NEET in the 10 years after leaving education for the first time. Our method produces six meaningful distinctions, as can be seen in Figure 2.6. The accompanying status proportion plots are shown in Figure 2.7.

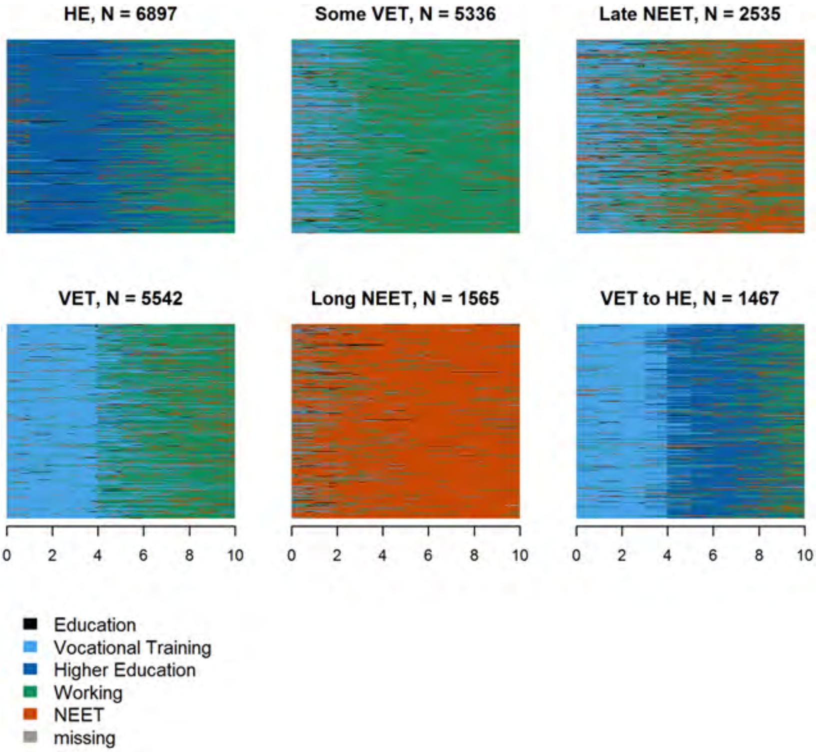


Figure 2.6: Index plots of NEET patterns in the Netherlands. Source: Statistics Netherlands, own calculations.

The first cluster (HE, N = 6897) represents 30% of individual trajectories of school-leavers who follow a typical higher education trajectory after leaving secondary education. The sequences in this trajectory are characterized by very short and infrequent NEET episodes during the school-to-work transition and most people in this cluster eventually end up in employment. On average, they spent 64.8 months in Higher Education, 35.2 months in Work, and only 8.6 months NEET. The following clusters mostly describe different trajectories through VET. The first of these clusters (Some VET, N = 5336, 23%) represents a trajectory of finding employment relatively soon (for a total average of 79 months) after secondary education and some vocational training (on average 14.8 months). However, on average people in this trajectory are NEET for a total duration of 13.7 months. Another relatively straightforward trajectory is represented by VET (N = 5542, 24%). This represents the classical vocational training trajectory. Many people follow this trajectory successfully into employment. On average, they spend 53.4 months in VET, 45.2 months in Work, and only 8.6 months NEET. Another VET-related cluster groups people who first follow VET, then transition to higher education, and then to the labor market (VET to HE, N = 1467, 6%). These mostly represent the usual routes through the Dutch education system, described in Section 2.1.2

We find two distinct trajectories consisting predominantly of NEET states. First, Long NEET (N = 1565, 7%), in which more than half become NEET shortly after secondary education and do not integrate into the labor market. Some first go through some short VET or have short employment episodes, but the vast majority of youth in this cluster stay in NEET for the rest of the 10-year observation period (on average 93.3 months). Second, Late NEET (N = 2535, 11%) who first go through VET (on average 32.5 months), then go through some short spells of employment, and then generally (about 60%) end up NEET (on average 46.9 months).

Table 2.2 gives a detailed description of the clusters in terms of socio-demographic composition. The higher education cluster has the highest share of women (55.8%). The two problematic NEET clusters have an about equal gender distribution. As expected, those who leave education without a starting qualification are overrepresented in the Long NEET and Late NEET clusters, with Late NEET to be most likely those that leave education with a VMBO diploma, while those who leave school without a diploma are overrepresented in the Long NEET cluster. Immigration background also correlates with being in a Long or Late NEET cluster. Interestingly, second generation immigrants are more likely to be in problematic NEET clusters than first generation immigrants. Socioeconomic background also matters and compared to the other clusters, youth in the Late and Long NEET clusters are more likely to come from families with parents that do not work, live in a rental house, and have lower incomes.

Table 2.2: Summary statistics across clusters

	HE		Late NEET		Long NEET		Some VET		VET to HE		VET		Total	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Gender														
Male	3.046	44,2	1.262	49,8	773	49,4	3.060	57,3	700	47,7	2.910	52,5	11.751	50,3
Female	3.851	55,8	1.273	50,2	792	50,6	2.276	42,7	767	52,3	2.632	47,5	11.591	49,7
School leaving diploma														
No diploma	48	0,7	669	26,4	1.015	64,9	1.276	23,9	246	16,8	722	13,0	3.976	17,0
HAVO/VWO	6.597	95,7	62	2,4	64	4,1	617	11,6	91	6,2	160	2,9	7.591	32,5
VMBO	252	3,7	1.804	71,2	486	31,1	3.443	64,5	1.129	77,0	4.660	84,1	11.774	50,4
Immigration background														
Native	5.715	82,9	1.541	60,8	1.097	70,1	4.447	83,3	1.109	75,6	4.240	76,5	18.149	77,8
1st Generation	230	3,3	315	12,4	119	7,6	200	3,7	76	5,2	330	6,0	1.270	5,4
2nd Generation (one parent)	952	13,8	679	26,8	349	22,3	689	12,9	282	19,2	972	17,5	3.923	16,8
Father's employment status (Age 16)														
Working (or Education)	6.060	87,9	1.603	63,2	926	59,2	4.236	79,4	1.187	80,9	4.369	78,8	18.381	78,7
Unemployment/Welfare benefits	196	2,8	259	10,2	177	11,3	281	5,3	70	4,8	254	4,6	1.237	5,3
Sickness/Other benefits/Pension/no income	356	5,2	334	13,2	244	15,6	446	8,4	117	8,0	516	9,3	2.013	8,6
Not in registers	285	4,1	339	13,4	218	13,9	373	7,0	93	6,3	403	7,3	1.711	7,3
Mother's employment status (Age 16)														
Working (or Education)	4.940	71,6	1.219	48,1	645	41,2	3.220	60,3	948	64,6	3.376	60,9	14.348	61,5
Unemployment/Welfare benefits	243	3,5	487	19,2	341	21,8	486	9,1	103	7,0	523	9,4	2.183	9,4
Sickness/Other benefits/Pension/no income	1.623	23,5	773	30,5	524	33,5	1.533	28,7	390	26,6	1.545	27,9	6.388	27,4
Not in registers	91	1,3	56	2,2	55	3,5	97	1,8	26	1,8	98	1,8	423	1,8
Household home ownership (Age 16)														
Owned	5.587	81,0	1.042	41,1	592	37,8	3.038	56,9	1.017	69,3	3.338	60,2	14.614	62,6
Rented w/ subsidies	463	6,7	846	33,4	574	36,7	897	16,8	200	13,6	982	17,7	3.962	17,0
Rented	847	12,3	647	25,5	399	25,5	1.401	26,3	250	17,0	1.221	22,0	4.765	20,4
Province														
Drenthe	236	3,4	95	3,7	51	3,3	150	2,8	50	3,4	214	3,9	796	3,4
Flevoland	145	2,1	100	3,9	41	2,6	182	3,4	38	2,6	160	2,9	666	2,9
Friesland	269	3,9	118	4,7	52	3,3	202	3,8	82	5,6	262	4,7	985	4,2
Gelderland	815	11,8	275	10,8	185	11,8	607	11,4	170	11,6	658	11,9	2.710	11,6
Groningen	229	3,3	92	3,6	94	6,0	119	2,2	65	4,4	241	4,3	840	3,6
Limburg	493	7,1	181	7,1	111	7,1	354	6,6	94	6,4	363	6,5	1.596	6,8
Noord-Brabant	998	14,5	327	12,9	211	13,5	903	16,9	209	14,2	753	13,6	3.401	14,6
Noord-Holland	1.139	16,5	397	15,7	217	13,9	833	15,6	226	15,4	819	14,8	3.631	15,6
Overijssel	479	6,9	143	5,6	119	7,6	322	6,0	109	7,4	435	7,8	1.607	6,9
Utrecht	555	8,0	170	6,7	100	6,4	378	7,1	93	6,3	376	6,8	1.672	7,2
Zeeland	144	2,1	52	2,1	30	1,9	121	2,3	31	2,1	126	2,3	504	2,2
Zuid-Holland	1.395	20,2	585	23,1	354	22,6	1.165	21,8	300	20,4	1.135	20,5	4.934	21,1
Household income (Age 16), Mean (SD)	47786.00	(28350.13)	31234.13	(15622.99)	29667.89	(14399.23)	35851.12	(18294.04)	39823.62	(19006.92)	36028.43	(17539.23)	38753.49	(22127.25)
Total	6.897		2.535		1.565		5.336		1.467		5.542		23.342	

Source: Statistics Netherlands, own calculations.

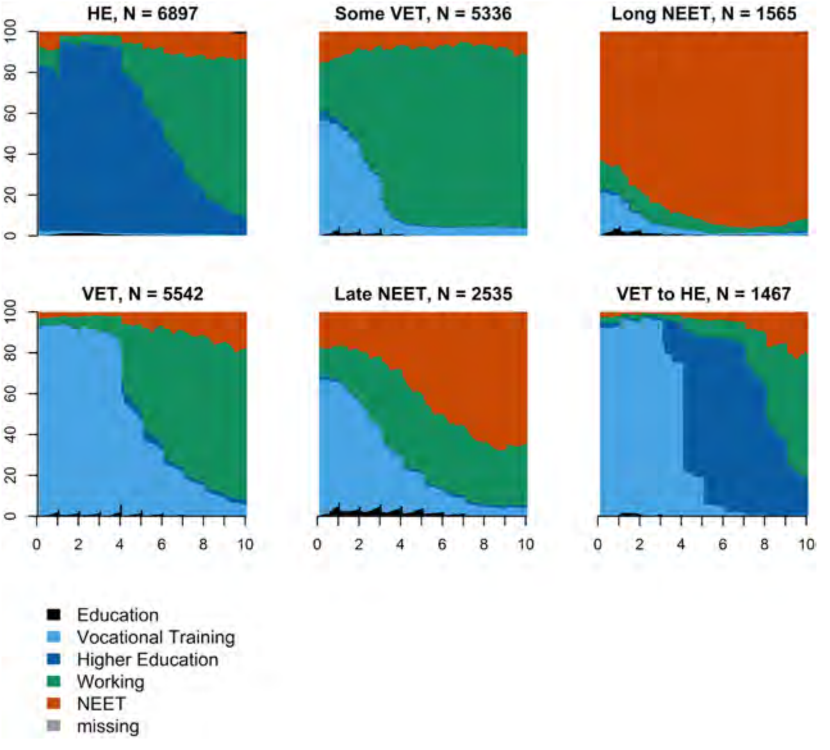


Figure 2.7: Status proportion plots of NEET patterns in the Netherlands. Source: Statistics Netherlands, own calculations.

2.4.3 Multinomial regressions: explanations of Dutch NEET patterns

The sequence analyses have revealed a typology of six meaningfully distinct patterns of labor market entry trajectories with at least one month of NEET. In this section, we analyze whether certain trajectories are associated with characteristics of the individuals. To answer this question, we estimate a multinomial logistic regression model in which cluster memberships are dependent variables and demographic and socioeconomic characteristics of school-leavers are independent variables. In these analyses, the reference category is the group of individuals that never experience an episode of NEET that lasts over one month during the 10 years after leaving school. In the following, we present the average marginal effects for each of the relevant variables. We focus on describing membership of the most problematic clusters, i.e., Long NEET and Late NEET.

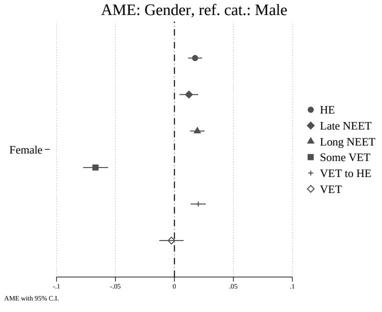
Figure 2.8 shows that there are some distinctly gendered patterns in the school-to-work transitions of school-leavers who experience at least one month of NEET. Women are more likely to follow a trajectory through higher education than men and are also more likely to follow a trajectory through VET and HE. They are considerably less likely to go straight to employment (after finishing some VET) than men. Most to our interest, and in line with our expectations, women are (slightly) more likely than men to follow Long NEET and Late NEET trajectories than men.

In Figures 2.8 and 2.8 we show that this is indeed partly due to the association between having a child during the school-to-work transition and the various trajectories. We find that having a child is associated with a higher likelihood of being in Some VET/early employment trajectory. Only after interacting child and gender is it that we find more pronounced associations. In Figure **??**, we see that women with children are not more likely long-term NEET but are more likely to become Late NEET. Men with children on the other hand are also less likely to become long-term NEET.

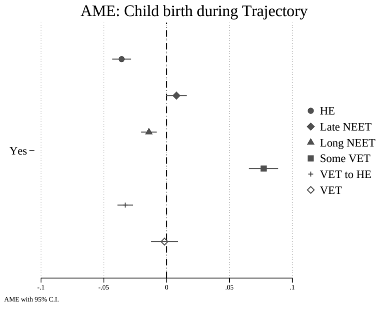
In Figure 2.9, the relationship between immigration background and the school-to-work trajectories is presented. Compared to natives, both first- and second-generation migrants are more likely to end up in Late NEET trajectories. This is in line with what we expected. Contrary to what we expected, however, immigrants are not more likely to be long-term NEETs.

Figure 2.10 shows the role of early school-leaving in the school-to-work transition. Here, the reference category represents those with a starting qualification (i.e., those with a HAVO, VWO or MBO level 2 diploma). Perhaps unsurprisingly, those with such diplomas are more likely to follow paths through higher education. As we expected, those with no diploma are more likely to follow NEET-trajectories that are problematic: Long NEET and Late NEET. Those who followed VET but did not achieve an earlier starting qualification are somewhat more likely to be Late NEET than those who have followed general education. Differences are rather small, however.

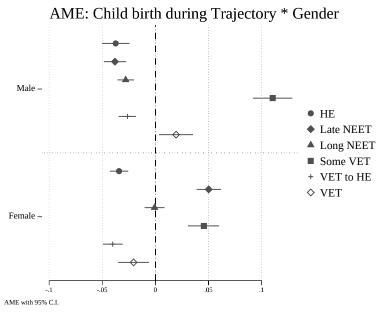
Our analyses suggest that intergenerational factors do play a role in explaining problematic school-to-work transitions in the Netherlands. Figure 2.11a presents the role of the father's employment status in the school-to-work transitions of young school-leavers who experience at least one month of NEET. Working fathers form the reference category. Compared to having a working father, all other categories are associated with a higher risk to become Late NEET and Long NEET. However, the size of the associations is modest and not larger than that of gender or immigration background.



(a) Gender



(b) Child



(c) Interaction

Figure 2.8: Average marginal effects of gender, child birth, and their interaction on school-to-work trajectories. Source: Statistics Netherlands, own calculations.

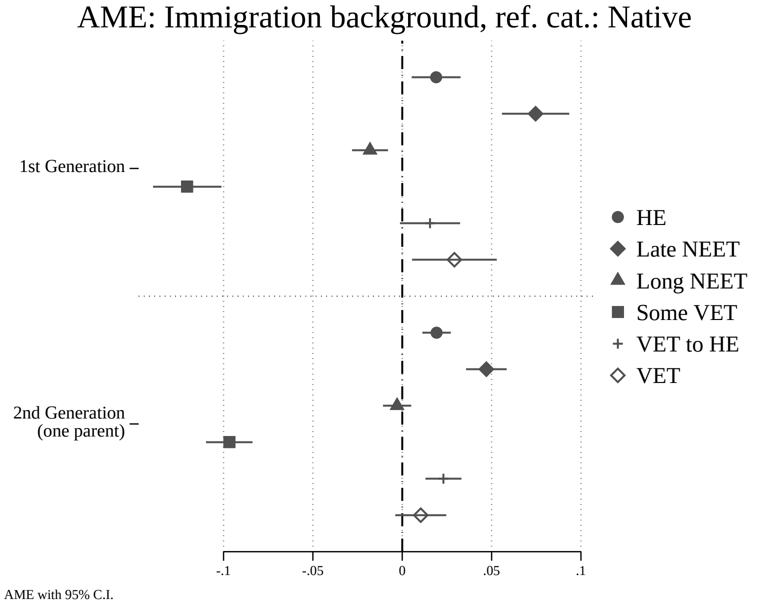


Figure 2.9: Average marginal effects of immigration background on school-to-work trajectories. Source: Statistics Netherlands, own calculations.

In Figures 2.11b and 2.11c, the relationships between NEET trajectories and homeownership as well as household income are shown. Compared to those whose parents own a house, those who live in a rented house are more likely to experience problematic school-to-work patterns Late NEET and Long NEET. Regarding household income, those whose parents have had higher incomes during youth are less likely to be in the Late NEET and Long NEET clusters. Now that we have discussed the sorting of young people into the different trajectories bases on their individual characteristics, we can ask whether the same variables also explain the length of the NEET period in the Netherlands.

Figure 2.12 shows the same variables just discussed used to explain the total number of months spent in NEET during the 10-year observation window. From this analysis, we can see that especially early school-leaving is an important correlate of long-term NEET trajectories. Furthermore, youth with an immigratio background are slightly more likely to be Long

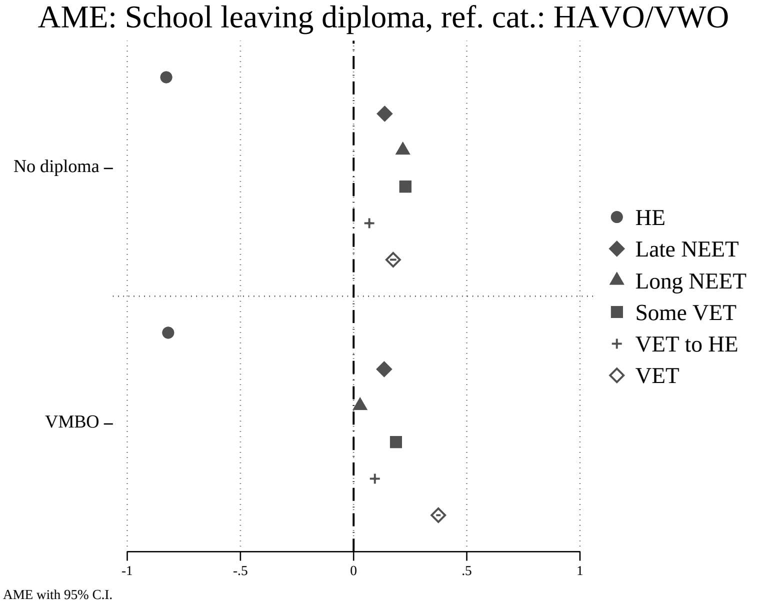
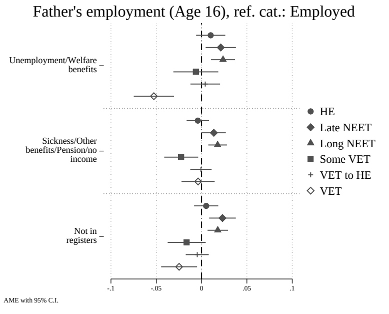


Figure 2.10: Average marginal effects of early school-leaving on school-to-work trajectories. Source: Statistics Netherlands, own calculations.

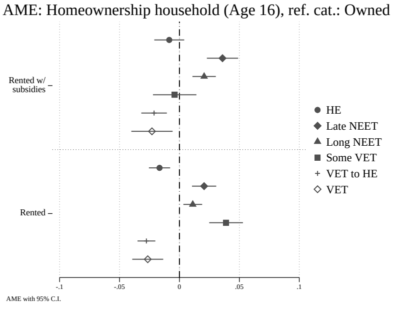
NEET, as well as those with parents who are unemployed and live in rental housing.

2.4.4 Income differences of NEET patterns

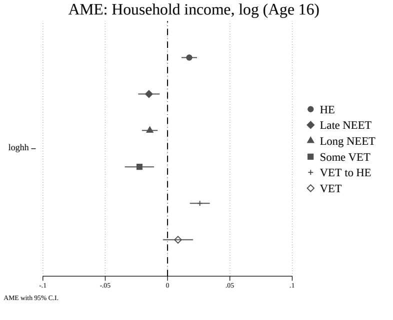
Finally, we want to explore whether cluster membership during the school-to-work transition predicts wage differences later in life. Figure 2.13 shows that at age 30 those young people who were either Long NEET or Late NEET during the school-to-work transition have a considerably lower monthly salary than those who follow more standard trajectories. For the other clusters we do not see such scarring effects.



(a) Father's employment



(b) Parental homeownership



(c) Parental household income

Figure 2.11: Average marginal effects of paternal employment, parental household homeownership and household income on school-to-work trajectories. Source: Statistics Netherlands, own calculations.

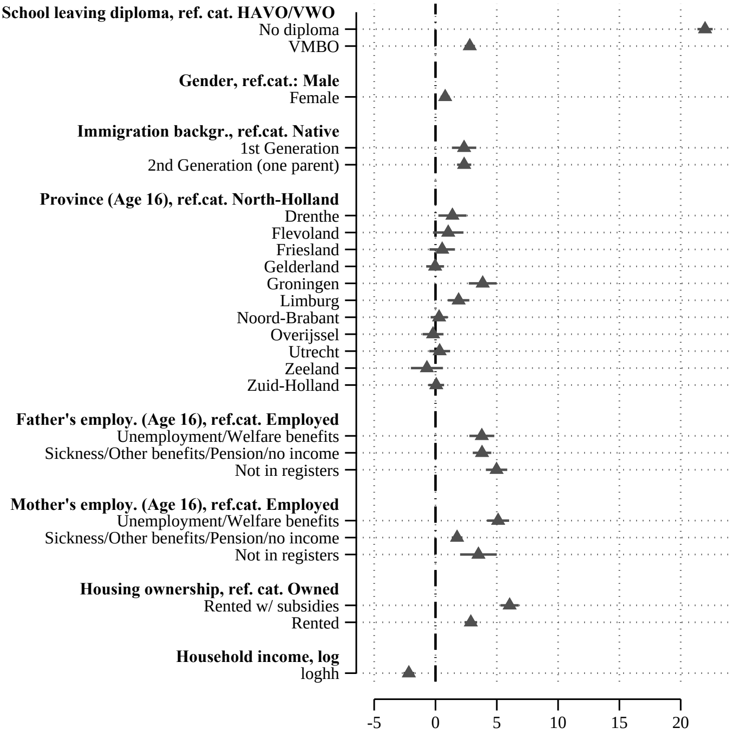


Figure 2.12: Linear regression of NEET months during ten years after leaving school. Source: Statistics Netherlands, own calculations.

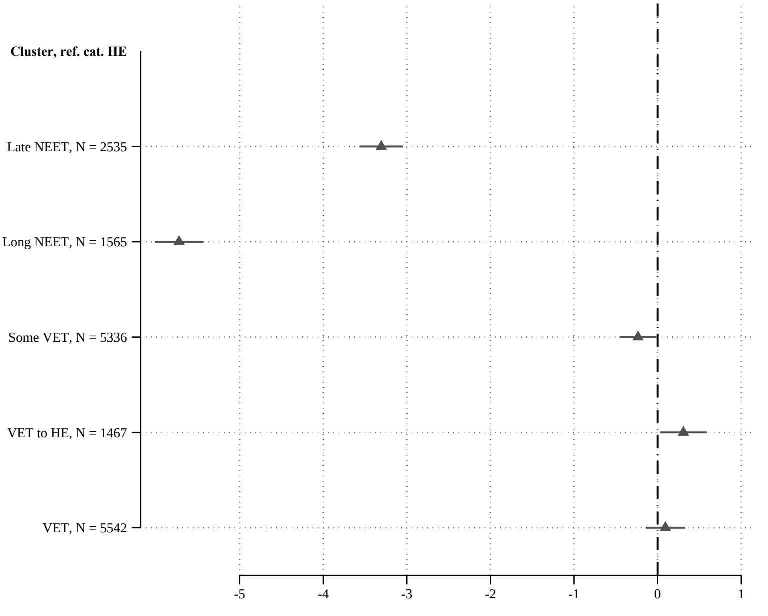


Figure 2.13: Linear regression of income at age 30 on NEET trajectories. Source: Statistics Netherlands, own calculations.

2.5 Conclusion

In this chapter we explored school-to-work and NEET patterns of young people in the Netherlands. We should interpret the findings in this chapter against the backdrop of the Dutch institutional context. The Netherlands has a highly stratified educational system, that tracks pupils relatively early. Selection is mainly done based on standardized high-stakes tests. The Dutch labor market is an occupational labor market, with a high level of employment protection. Welfare benefits are generally not available for school-leavers, and family policies may contribute to gender-specific patterns in the school-to-work transition.

We first estimated logistic regression models to see which personal characteristics explain experiencing at least one month of NEET during the school-to-work transition. These analyses suggested that early school-leavers are much more likely to be NEET for at least a month. We found that first-and second-generation immigrants are more likely to experience one month of NEET than Dutch natives. Young women are only slightly more likely than men to experience one month of NEET. We also found indications for the relevance of social backgrounds: those with unemployed fathers and those living in rental houses are more likely to experience NEET.

We then focused on youth who experienced at least one month of NEET status and used sequence analysis to identify clusters of typical trajectories. We found six clusters. By far most youth who experienced one month of NEET status actually have a fairly normal school-to-work transition. Only 6.7% of all youth who experience NEET status can be considered long-term NEET. Another 10.9% are potentially problematic, as they become NEET later in the school-to-work transition. Since our data are right censored, they may actually become long-term NEET later on. Taken together, about 18% of all Dutch youth who experience NEET are to be considered potentially problematic. Compared with similar analyses in Levels et al. (2022), the Netherlands ranks a bit higher than France (about 13% of NEET are long-term), Germany (about 12%), and England (16.9%). Only in Japan, more school-leavers become NEET later (15%) or for the long-term (17%).

We found that women are more likely than men to experience long-term NEET and later NEET trajectories than men. As we expected, this seems to partly be a motherhood penalty. While young women with children are not more likely to become long-term NEET, they are more likely to become Late NEET. This is in line with the fact that Dutch women have their first child relatively late. However, because the data are right-censored, they might also be classified as long-term NEET over time. Interestingly, and also in line with our expectations, men with children on the other hand are also less likely to become long-term NEET. This corresponds with the dominance of the male breadwinner model. We also found that migrants are more likely to experience Late NEET trajectories but not more likely to be long-term NEETs. As expected, early school-leavers (those without a starting qualification) are much more likely to follow NEET-trajectories that are problematic: Long NEET and Late NEET. Early school-leaving is actually the strongest predictor of problematic transitions (for a comprehensive analysis of early-school leaving in the Netherlands, see Traag, 2012). Finally, family background and intergenerational factors also contribute to problematic school-to-work transitions in the Netherlands. In fact, parental unemployment seems to be partly intergenerationally transmissible to children. Finally, our analyses also suggest that being long-term NEET or Late NEET during the school-to-work transition has considerable scarring effects: youth in these groups earn a much lower salary at age 30.

Chapter 3

From School to Where? How Social Class, Human Capital, Aspirations, and Resilience explain unsuccessful School-to-Work Transitions[1]

3.1 Introduction

A lot is at stake for youth during the school-to-work transition. According to the life course principle of *human agency*, they are required to "construct their own life course through the choices and actions they take within the opportunities and constraints of history and social circumstances" (Elder, 1998, p. 4). Yet, some youths do not succeed in making this transition. As also shown in Chapter 2, a disrupted school-to-work transition has important negative consequences for later life outcomes, including but not

[1]This chapter was joint work with Mark Levels and Rolf van der Velden and published as ROA Research Memorandum 2020/05. We thank the editor Hans Heijke, and the reviewers, Per Bles and Davey Poulissen, for their valuable comments on the manuscript. We also like to thank our colleagues of the ORA Understanding NEETs project as well as participants of the RC28 conference in Seoul, who all gave valuable comments on the manuscript at different stages. An earlier version of this chapter was published in Dutch language as Dicks, Alexander, Mark Levels, and Rolf van der Velden. 2018. "Van school, en dan wat? Sociale klasse, menselijk kapitaal en persoonlijkheid en een problematische overgang van school naar werk." *Tijdschrift voor Arbeidsvraagstukken*, 34(4). We thank the editors of the special issue, Wendy Smits & Anet Weterings, and the anonymous reviewers for their valuable comments.

limited to wage scars, low re-entry rates, and well-being (Bell & Blanchflower, 2011; Bynner & Parsons, 2002; Gregg & Tominey, 2005; Luijkx & Wolbers, 2009; Oreopoulos, 2007). Understanding why some youth fail to make this transition is paramount for designing policies to prevent this. In the previous chapter, we already explored several mechanisms. In this chapter, we build on these efforts and investigate how social class, human capital, personality, and occupational aspirations predict an unsuccessful school-to-work transition in the Netherlands. We are among the first to study those in concert while at the same time having high quality, longitudinal register data about the complete school-to-work transition until age 30. We aim to explain why some young people experience a school-to-work transition that is characterized by recurrent, significant periods in which they were **N**ot in **E**mployment, **E**ducation, or **T**raining (NEET).

The risk of becoming NEET is often associated with key variables in status attainment models: cognitive skills, education, and social class. Cognitive skills and education are rewarded on the labor market. However, because they are difficult to observe, potential employers use educational degrees as signals. As such, young people with low cognitive skills or no educational degree would likely struggle on the labor market (Bynner & Parsons, 2002; McVicar & Anyadike-Danes, 2002; Shavit & Müller, 1998; van der Velden & Wolbers, 2007). Social class, or the role of parental background, has also been well-established to matter for the school-to-work transition where children from higher social backgrounds are better able to make the school-to-work transition (Bynner & Parsons, 2002; Caspi et al., 1998; Coles et al., 2002; Furlong & Biggart, 1999; Sewell et al., 1969; Staff & Mortimer, 2008; Thompson, 2011). However, human capital and social class are likely not the only factors that could explain unsuccessful transitions.

One important factor may be young people's aspirations. Occupational aspirations play a major role in youths' occupational development (Schoon & Parsons, 2002). Not having clearly defined aspirations on the other hand can be detrimental for labor market integration (Holtmann et al., 2017; Sabates et al., 2011; Staff et al., 2010; Vuolo et al., 2012; Yates et al., 2011). Despite this, many young people do not have a clear idea of what they want to become. Some do not know which occupation to pursue (Sabates et al., 2011; Staff et al., 2010; Yates et al., 2011) while others refuse to make choices or do not want to commit to them (Du Bois-Reymond, 1998). However, even if they have a concrete aspiration, that does not mean that it is a realistic one. Youth who aspire to an occupation that does not align with their educational qualifications and expectations and who set their bar too high or too low might struggle just the same (Croll, 2008; Sabates et al., 2011).

Another factor is personality. Many studies have shown the importance of personality and other non-cognitive skills on the labor market (Borghans et al., 2008; Gelissen & de Graaf, 2006; Heckman, 2006; B. W. Roberts et al., 2007; Uysal & Pohlmeier, 2011). Hence, the extent to which people are able to make a successful school-to-work transition is likely related to personality as well. In this context, personality traits are usually interpreted as non-cognitive skills that are rewarded on the labor market (Bowles et al., 2001). However, for youth at risk to become NEET, the extent to which they are resilient enough to overcome setbacks during the school-to-work transition and are able to adapt to new situations might be more important (Ng-Knight & Schoon, 2017; Nieuwenhuis et al., 2016; Pinquart et al., 2003).

While we can expect that human capital, social class, aspirations, and personality are all important for the school-to-work transition, research exploring their role has largely developed along separate lines (Damian et al., 2015). This might be problematic, as the four factors are intricately wound up. The following three examples lay out this issue. Firstly, the development of career identities and – by extension – unclear aspirations are mediators of a psychological process (Burns et al., 2013; Germeijs & Verschueren, 2011; Guay et al., 2003; Hirschi, 2012; Martincin & Stead, 2014; Tokar et al., 1998). Second, parents of higher social class might know better than parents of lower social class, which personality traits are rewarded by the school system and the labor market and then foster such skills in their children (Bowles et al., 2001; Farkas, 2003; Shanahan et al., 2014). Third, social class is also mediated through education and cognitive skills. Assuming that all parents want their children to at least maintain their social class, parents from higher social classes have to make sure their children attend the highest school tracks (Boudon, 1974; Erikson et al., 2005). In addition, they likely have access to better information about the school system, partly due to their own experience (Pfeffer, 2008).

To better understand how personality and aspirations shape the school-to-work transition, we study their effects in conjunction. We address the following research question: *to what extent and how do human capital, social class, personality, and aspirations predict a school-to-work trajectory that is predominantly characterized by time spent in NEET?*

We combine high-quality administrative data from the Social Statistical Database (SSD) of Statistics Netherlands (CBS) (Bakker et al., 2014) with the Secondary Education Student Cohort Survey from 1999 (VOCL'99) (Kuyper et al., 2003). The VOCL'99 provides us with measures of aspirations and five-factor personality inventory measures (Hendriks et al., 1999b). We analyze these data in two steps. First, we use sequence analysis to explore different school-leaving trajectories into and out of work, education, and

NEET. Sequence analysis is especially suited for this task because it does not assume a data generating process and does not underrepresent irregular careers (Aisenbrey & Fasang, 2010). Register data are especially useful to study small groups and phenomena of low incidence and are optimal for sequence analysis because they offer detailed longitudinal data without recall bias or panel attrition (Bäckman & Nilsson, 2016; Bakker et al., 2014). Secondly, we use multinomial regression to test our hypotheses about unsuccessful school-to-work transitions and to explain selection into the trajectories.

Our research is first and foremost informative about the way in which unsuccessful trajectories from school to work should be understood. One of the main problems of the NEET definition is that it lumps together various groups of people, who may be inactive on the labor market for very different reasons. Clearly, lumping together different groups of youth under one umbrella term obscures important differences (Furlong, 2006; Maguire, 2015; Yates & Payne, 2006). Young people traveling and taking a gap year likely differ fundamentally from youth who are inactive because their skills are not demanded on the labor market. Efforts to explain why and who becomes NEET mostly focused on identifying different predictors of NEET as a state (Eurofound, 2016). However, studying NEET at a single point in time does not help to uncover the diversity of this group. One needs to take a life course perspective and study trajectories longitudinally.

As indicated above, this chapter uses a unique combination of survey data and register data, allowing us to have detailed information on these trajectories. The availability of such data in the Netherlands offers a strong comparative advantage to properly test hypotheses about the school-to-work transition, but there is also a substantial reason for focusing on the Dutch case. The NEET rate in the Netherlands is the lowest in the European Union (Eurofound, 2012). Hence, young people who become NEET might be especially negatively selected and vulnerable. In no other European country does disability account for economic inactivity to the extent it does in the Netherlands (Eurofound, 2016). Given that Dutch young people who become NEET are relatively irresponsive to active labor market policies (Cammeraat et al., 2017), it seems unlikely that the standard human capital explanation alone can explain becoming NEET. Additional explanations have to be explored, which we do in this chapter. On the other hand, young people who become NEET in the Netherlands have a relatively low risk of social exclusion compared to other countries in Europe (Eurofound, 2016). We should thus expect considerable heterogeneity in school-to-work transitions which we aim to explain. It is to these explanations that we turn in the next section.

3.2 Theory

The school-to-work transition is a transformative rite of passage, marking school-leavers' transition from being predominantly in education to being predominantly active on the labor market. However, this is only reality for a limited number of people. For many, the school-to-work transition is not so much a transition as it is a trajectory (Brzinsky-Fay, 2014) or pathway (Shanahan, 2000). Meaning, rather than experiencing a single event which marks the end of school and the beginning working life, they experience a much messier transitory phase of switching back and forth between various states (Kerckhoff, 2003). While some might find short-term jobs right out of school and then become NEET for some time until they find a more stable job, others might be NEET for a short time and then go back to school to earn additional qualifications. However, some might become long-term NEET or follow a volatile trajectory that is characterized by frequent and recurring NEET spells. It is these unsuccessful and likely volatile school-to-work trajectories that interest us here. In this section, we will derive hypotheses from various theories to explain them. Given the demonstrated scarring-effects of problematic school-to-work transitions (Gregg & Tominey, 2005; Schmillen & Umkehrer, 2017; Steijn et al., 2006), we interpret a school-to-work transition characterized by frequent and significant spells of NEET as problematic (see also Chapter 2).

So, what explains becoming NEET? We argue that we need to unpack NEET before we can explain it. The concept was mostly defined and developed by policymakers and lumps together young people that are NEET for widely different reasons (Furlong, 2006; Maguire, 2015; Yates & Payne, 2006). Not only has the term as such been criticized, but also the literature on NEET is generally relatively light on theoretical explanations. For instance, NEET is very much related to early-school leaving, youth unemployment, and the school-to-work-transition in general. All of which have been studied extensively. We can draw on this rich literature and their theories to further our knowledge of NEET.

3.2.1 Social Class

Social class background has long been shown to influence labor market success and related outcomes of the status attainment process. Most theories describe social class as the underlying cause of other inequalities which then translate to inequalities in labor market outcomes. First, via education, because children from higher social backgrounds fare better in education and make different educational choices than their lower-class peers (Boudon, 1974; Bourdieu & Passeron, 1977; Erikson et al., 2005). Second, because they have higher and better aligned aspirations or at least can make up for a lack of orientation (Croll, 2008). Third, because they have more cultural (Bourdieu & Passeron, 1977) and social capital (Coleman, 1988; Lin, 2001; van Tubergen & Volker, 2014; Verhaeghe et al., 2013). Fourth, because the knowledge of parents is often based on their own education and employment history. Hence, parents who themselves did not attend the academic tracks or higher education, or have been unemployed, can give less advice regarding these topics to their children (cf. Pfeffer, 2008). All these resources help young people to achieve educationally and to find employment. We thus expect an effect of social class:

> *Hypothesis 1: Youths from higher the socioeconomic backgrounds are less likely to experience a trajectory predominated by NEET spells than youths from lower socioeconomics backgrounds.*

3.2.2 Human Capital

Widely recognized are the effects of educational credentials and skills, i.e., human capital, on the labor market. Employers seek out the most qualified employees in an intricate matching process (Logan, 1996). Education and skills are an investment which is rewarded on the labor market (Becker, 1964). Because ability is usually unobserved, educational degrees act as signals of ability (Spence, 1973). Empirically, low-achieving school-leavers often have difficulties in successfully entering the labor market (Brzinsky-Fay & Solga, 2016; Bynner & Parsons, 2002; McVicar & Anyadike-Danes, 2002; Shavit & Müller, 1998; van der Velden & Wolbers, 2007). We thus expect that:

> *Hypothesis 2a: Youths from higher secondary education tracks are less likely to experience a trajectory predominated by NEET spells than youths from lower secondary education tracks.*

As well as:

> *Hypothesis 2b: The higher the cognitive skills of youths, the less likely they experience a trajectory predominated by NEET spells.*

3.2.3 Aspirations

Stratified and occupational-specific education systems like the Dutch system allocate young people to the labor market in two ways. First, by sorting them into vocational or academic tracks. Second, and especially in the vocational track, by providing them with a specific skill set to be productive in the early career. Pupils in such systems have to make a number of important decisions early on. By deciding on courses and specialization, they also decide which skills to focus on, and on what level. In making these decisions, they shape their future, and prepare themselves for the transition to the labor market. However, they also make these decisions in the context of their aspirations. Aspirations are formed through a process of 'circumscription and compromise', and transmit their interests, social class, their subjective perception of opportunities, and gender (Gottfredson, 1981).

Having clear aspirations might help pupils to set an educational course for themselves. Being uncertain about their aspirations may keep pupils from making sufficiently informed decisions, which could end in a much more volatile school-to-work trajectory. Previous evidence suggests that uncertain aspirations increase the probability to attain lower levels of education (Sabates et al., 2011), to become NEET (Yates et al., 2011) and to earn lower wages (Sabates et al., 2011; Staff et al., 2010).

Therefore, we expect that:

> *Hypothesis 3a: Youths with uncertain aspirations are more likely to experience a trajectory predominated by NEET spells than youths with certain aspirations.*

Another aspect of aspirations is whether they are realistic and attainable. Youth who aspire to have a job for which they underestimate the education requirements, will most likely face issues during the school-to-work transition (Croll, 2008; Sabates et al., 2011). For this reason, we expect that:

> *Hypothesis 3b: Youths whose occupational aspirations align with their educational expectations are less likely to experience a trajectory predominated by NEET spells.*

3.2.4 Personality

The relation between personality and labor market outcomes has been researched extensively (for reviews see Borghans et al., 2008; Farkas, 2003; B. W. Roberts et al., 2007). In this literature, usually five traits are distinguished (i.e., openness [or in the data we use, autonomy], neuroticism, extraversion, agreeableness, and conscientiousness), and then related to

Table 3.1: Alignment typology adapted and extended from Sabates et al (2011)

Educational expectations	Occupational aspirations		
	Professional	Nonprofessional	Don't know/ missing
Academic	I. Aligned (High) 12%	II. Misaligned (Over) 8%	III. Academic uncertain 20%
Vocational	IV. Misaligned (Under) 1%	V. Aligned (Low) 5%	VI. Vocational uncertain 6%
Don't know/ missing	VII. Uncertain professional 7%	VIII. Uncertain nonprofessional 12%	IX. Orientation less 28%

labor market outcomes. Although widely accepted, the conceptualization of personality as traits (the so-called variable-centered approach) has theoretical as well as empirical downsides. While correlations of single personality traits and outcomes are well established empirically, theoretically these links are not always clear-cut and invite post-hoc explanations. The variable-centered approach obfuscates that single personality traits do not exist in isolation. Personality traits are in fact manifest approximations of the latent factor personality which itself is a hierarchical system of subcomponents that interact within persons (Ferguson & Hull, 2018; McCrae & Costa, 1987). Hence, empirically, personality traits covary and account for shared variance therewith concealing mutual influences. All the while interactions of five variables are difficult to model and interpret (Merz & Roesch, 2011). Therefore, we use a conceptualization of typologies of personality traits which represent combinations of various personality traits within a person (person-centered approach), thereby approximating such interactions (Ferguson & Hull, 2018; Lanza et al., 2010; Merz & Roesch, 2011). The most common personality typologies distinguish "Resilient/Well-adjusted", "Undercontrolled", "Reserved" and "Overcontrolled/Excitable" types (Block & Block, 1980; Ferguson & Hull, 2018). Resilient/Well-adjusted individuals score positive (socially desirable) on all five personality traits (Asendorpf et al., 2001; Ferguson & Hull, 2018; Robins et al., 1996). They tend to do well in education (Robins et al., 1996), are well-adjusted and can easily adapt to changing and uncertain environments (Akse et al., 2004; Asendorpf et al., 2001). Hence, being resilient is a prime asset during the transition to adulthood. For example, resilient boys leave the parental home earlier and resilient girls find (part-time) jobs earlier (Dennissen et al., 2008). Because resilient youth are expected to be more able to cope with the uncertainties and stress during the school-to-work transition, we hypothesize that:

> *Hypothesis 4: Resilient youths are less likely to experience a trajectory predominated by NEET spells than non-resilient youths.*

3.2.5 Mediation

As we argued before, all these factors likely act in concert. First, social class background is a key variable in the formation of children's personality as parents might foster specific personality traits in their children (Farkas, 2003). Second, parents are likely to guide their children in their occupational choices (Croll, 2008). Third, and most straightforward, is the link from social class to labor market success via education (Boudon, 1974; Bourdieu & Passeron, 1977), where children of higher educated parents perform better in school and their parents can assist them in other schooling related matters and decision-making.

Hence, we expect that:

> *Hypothesis 5: The effect of social class is mediated by (a) education, (b) personality, and (c) the alignment of occupational aspirations.*

3.2.6 Moderation

Not only are education, personality, and aspirations mediators of social class, they could also compensate for the lack of resources that parents from a lower socioeconomic background can offer their children (Mirowsky & Ross, 2003; Ng-Knight & Schoon, 2017; Shanahan et al., 2014). If, say, a child from lower-class background has very clear goals about the future and is doing well in school, or is resilient against stress and setbacks, the negative effect of social class might become less strong. Hence, we expect that:

> *Hypothesis 6: The effect of social class is lower for youths who (a) were enrolled in the higher education tracks, (b) have a resilient personality, and (c) have aligned occupational aspirations.*

3.3 Data

To test our hypotheses, we use a combination of register and survey data. We use the VOCL'99 data collected from a random sample of pupils in the first year of secondary education in 1999 (Kuyper et al., 2003). Sampling for the VOCL'99 was done on the school level. From 1144 school locations in the Netherlands, 246 were randomly selected. From these 246, 126 school locations agreed to participate. Within these 126 school locations, there were 825 first grade classes in which were 19,391 pupils. These represent about 11% of that school entry cohort (Van Berkel, 1999). Data was collected from three sources: schools were asked to deliver background information on their pupils, pupils filled out questionnaires and ability tests and additional questionnaires were taken home by the pupils to be filled out by parents (in 147 cases by care takers). We link individuals from the VOCL'99 to the Social Statistical Database (SSD) (Bakker et al., 2014). The data provide information on the monthly activity of all persons registered in the Netherlands and allow us to construct detailed education and employment biographies for all pupils. We can identify N = 19,291 of our original sample in the administrative data using the personal identifier variable supplied in the VOCL and subsequently match and observe labor market and education trajectories for 19,284 individuals from January 2001 until December 2018. For the sequence analysis, we restrict the sample to those who have valid data for at least 90% of the episodes under observation (N = 18,435). We then perform listwise deletion on our variables of interest so that our final analytical sample is N = 10,955. Some missing data stem from the parental questionnaire which unfortunately has sometimes not been filled in. Still, we have to rely on the parental questionnaire for parental education because education was not yet properly measured in the administrative data for that cohort. Some missing data also stem from the personality items, which have lower response rates than the rest of the questionnaire.

Table 3.2: Descriptive statistics

Variable	Mean/ Percentage	SD	N
Gender			
Male	49.16%		5,570
Female	50.84%		5,385
Immigration background			
Dutch	86.36%		9,461
First generation	2.67%		292
Second generation	10.97%		1,202
Age at leaving school	17.39	1.08	10,955
Track before leaving school			
Practical	6.54%		717
VMBO	37.10%		4,064
HAVO	26.91%		2,948
VWO	20.16%		2,209
Other	9.28%		1,017
Total score entry test	37.79	10.48	10,955
Personality traits			
Emotional stability	1.07	0.91	10,955
Extraversion	1.19	0.86	10,955
Conscientiousness	0.38	1.03	10,955
Agreeableness	1.75	1.10	10,955
Autonomy	0.48	0.86	10,955
Personality type			
Resilient	94.82%		10,387
Non-resilient	5.18%		568
Household status			
Two parents	92.53%		10,137
Single parent	6.85%		750
Care taker	0.62%		68
Parental education			
Primary	23.54%		2,579
Secondary	44.33%		4,856
Tertiary	32.13%		3,520
Parental joblessness history			
Never	51.77%		5,671

Continued on next page

Table 3.2 – continued from previous page

Variable	Mean/ Percentage	SD	N
1 - 2 years	26.33%		2,884
more than 2 years			
Household income in 1000€	42.54	22.95	10,955
Parental homeownership			
Owned	73.53%		8,055
Rented	26.47%		2,900
Months NEET 13 years after leaving school	11.54	24.11	10,955
Total N			10,955

Source: Statistics Netherlands, own calculations.

3.4 Measurements

We use the following variables in our analyses. Descriptive statistics of all variables are presented in Table 3.2.

Monthly activity sequence: The monthly activity is obtained by merging two datasets from the Dutch administrative data (SSD) (Bakker et al., 2014). The dataset SECMBUS includes calendar data on the main economic activity (variable SECM) based on the main source of income. While it is theoretically possible to receive a larger income from social welfare than from employment in practice this is seldom the case, and the income or workhours would have to be very low for this to happen. This variable has twelve states: (1) employee, (2) director/major share-holder, (3) self-employed, (4) other self-employed, (5) recipient of unemployment insurance, (6) recipient of welfare, (7) recipient of other social benefits, (8) recipient of illness and disability benefits, (9) recipient of pension, (10) (not yet) pupil/student with income, (11) (not yet) pupil/student without income, (12) other without income. We combine states 1-4 into 'Working', states 5-9 and 12 into 'NEET', and states 10-11 into 'Education'. The dataset STUDERENDENBUS includes calendar data on registration in publicly funded education (variable SOORTONDERWSTU). We combine the information from both datasets to distinguish secondary education from further education. We thus merge the two variables, whereas we let education overwrite other states. We do this because the analysis cannot handle simultaneous states. Following the paradigm of human capital and investment in skills, we view education as the more important state of the two. Primary education, practical education, and secondary education are grouped together as "Secondary Education and below". The other states represent the three main types of further education in the Netherlands, upper secondary vocational education (MBO), university of applied science (HBO), and research university (WO). Before 2004, there is less information available on the educational activity. That is especially the case for primary and special education as well as vocational training. In such cases, education attendance is assigned by Statistics Netherlands based on compulsory schooling age. From 2004 onwards, this is done less often. For our sample, that means that until the Age of 16 there might be some imputation but after that not anymore.

3.4.1 Social Class

Parental education: In the VOCL parental questionnaire, parents were asked to name their own and their partner's highest obtained educational degree. The highest of either answer refers to the highest obtained parental education, measured in categories from primary education to tertiary education. We use a collapsed version of the variable, distinguishing primary, secondary, and tertiary education (Bachelor equivalent degree or above).

Parental joblessness history: In the VOCL parent questionnaire, parents were asked to recall their own and their partner's employment history and the total duration spent without a job since the age of 15. Answers ranged from no joblessness history to more than ten years. We sum up the values of both partners and distinguish between "Never jobless", "1 to 2 years", and "More than 2 years".

Parental household income: Using the Social Statistical Database (Dataset INTEGRAAL HUISHOUDENS INKOMEN) we can link personal identifiers to households and have access to the yearly household income. We use the value from 2003 as it is the earliest available measurement. Some observations have negative values which we replace with €1[2].

Parental household homeownership: Using the same dataset used for the household income, we have information on the homeownership status of the household in 2003. The original variable distinguishes owned housing from rented with subsidies and rented without subsidies. As the receival of subsidies mainly relies on income which we already measure, we dichotomize the variable into owned (0) and rented (1).

[2]According to Statistics Netherlands, negative income values may occur as administrative errors. For example, companies may use it to correct a previous administration error. Another source of negative income values is self-employment. A value of 0 can occur as unpaid vacation. Source: private e-mail conversations.

3.4.2 Human Capital

Cognitive skills: In the VOCL study, pupils took a cognitive skills test in math (Cronbach's $\alpha = .83$), language (Cronbach's $\alpha = .74$), and information processing (Cronbach's $\alpha = .79$) (Kuyper et al., 2003). Values were assigned by CBS for students who only finished two of the three subdomains (Kuyper et al., 2003). For 1216 students who did not finish any subdomain and for 36 students who only finished one subdomain, no test data is available. The total score is recorded as variable RCTOT. This test was designed analog to the CITO exit test and as expected both correlate highly, $r = .82$, $p < .01$. The CITO test is used for tracking students after primary school and hence both RCTOT and CITO score correlate highly with the tracking advice given ($r = .78$, $p < .01$; $r = .82$, $p < .01$). We use the RCTOT variable as it has considerably less missing data (6.5% compared to 50.5%) than the CITO test variable ($N_{missingRCTOT} = 1252$; $N_{missingCITO} = 9792$). To aid interpretation we standardize the score of RCTOT to the sample mean after listwise deletion.

Last track enrolled: From the monthly activity variable described above, we take the educational track that the pupil was last enrolled in before leaving secondary school for the first time. Here, we also distinguish between general tracks giving access to higher education (HAVO and VWO) from vocational tracks (VMBO, coded as the reference category) as well as practical education. As described above, for some pupils, administrative data on the secondary school attendance was unavailable. There are cases of missing data on educational tracks prior to being first registered as in work, or NEET. There are also cases where Statistics Netherlands assumes pupils to be in school without additional information whether they really are (in case of missing data before the age of 16 in accordance with legal school age). Using the VOCL survey, we can alleviate these shortcomings to some degree. First, because we use the VOCL survey as our base sample, we are sure that at the time of the survey, all the observed pupils were enrolled in secondary education in the Netherlands. Second, from the VOCL survey we know which track a pupil was enrolled and can use this to verify the origin of the imputations. The majority of assigned cases was enrolled in the vocational track (VMBO) in 1999 (see Table A.4.2 in Appendix A.4 to this chapter).

3.4.3 Aspirations

Occupational aspirations: In the VOCL questionnaire, pupils were asked "Do you already know what you want to become later?" If answered yes, they were asked to name the occupation. To classify the occupations listed by the pupils, we performed exact matching of answers to the ISCO classification using text responses from the publicly available conversion tools provided by Ganzeboom and Treiman (2012). For unmatched answers, we removed typos and symbols and matched again. The unmatched answers were matched manually. We classify occupational aspirations as professional (ISCO major groups 1 & 2) or nonprofessional (ISCO major groups 3-10) as well as "Don't know" if the answer to the previous filter question was "No" or if the answer was "Yes" but no occupation was named by the pupil. We then combine the occupational aspiration with the *educational expectation* variable: students were asked "imagine you are going to continue learning, which education do you think you will follow?" Possible answers corresponded to the different tracks of the Dutch education system as well as "I don't know yet". Cross-tabulating the two gives us a measurement of how well a pupil assesses whether the aspiration is achievable. Table 3.1 gives an overview of the combinations.

3.4.4 Personality

Resilience: Personality traits were assessed in February 2001 when participants were 14 years old. The Five Factor Personality Inventory (FFPI) (Hendriks et al., 1999b) consists of 100 items to measure Extraversion, Agreeableness, Conscientiousness, Emotional Stability, and Autonomy. Responses were collected with a scale from 1 (not at all applicable) to 5 (entirely applicable). Data selection and cleaning was provided by Statistics Netherlands and relied on the standard FFPI scoring procedure (Hendriks et al., 1999b). That is, students were excluded if less than 70% of items were answered, responses were corrected for positive answering bias (acquiescence; 'yea-saying'), and missing values were imputed by the student's personal mean on the answered items per factor pole. We define resilience as above average values on Emotional Stability, Conscientiousness, Agreeableness, Autonomy, and Extraversion.

3.4.5 Control variables

Single parent: Parents were asked to give information on their marital status. We distinguish single parent households (coded as 1) from two-parent households (coded as 0). We also added a category indicating whether the parental questionnaire was filled-in by a caregiver rather than a parent. *Gender (female)*: Pupils were asked to name their gender. We recoded the variable to distinguish female pupils (coded as 1) from male pupils (coded as 0). *Immigration background:* The country of birth of pupils and parents was obtained from Dutch administrative records. We distinguish between pupils with two native born parents (coded as 0) from pupils who were not born in the Netherlands (First generation, coded as 1) and pupils with at least one foreign born parent (Second generation, coded as 2).

3.5 Analysis

We analyze these data in two steps. First, we use sequence analysis to identify clusters of trajectories that characterize Dutch pupils' transition from school to work. Then, we use logistic regression to predict cluster membership, and assess the extent to which certain sequences are more likely for people with certain personality types and aspirations. We use Stata 16 for estimation (StataCorp, 2019). To aid interpretation we present average marginal effects. To properly decompose direct and indirect effects of parental social class, we use the decomposition method described in Karlson & Holm (2011) and make use of the khb Stata-ado in Stata (Kohler et al., 2011).

3.5.1 Sequence analysis

Sequences consist of a finite set of categorical states: education, inactivity, and employment. Like a fingerprint, every person has an individual sequence pattern. However, because people are also part of the same institutional, social, and economic context, we can also expect similarities between trajectories. Ordering and identifying these similarities and inferring generalities from them is the main task of sequence analysis. To do so, we rely on the optimal matching algorithm to calculate a pairwise measure of dissimilarity given a pre-defined cost structure. We select the costs that are standard to optimal matching, where we set insertion/deletion costs as 2 and substitution costs as 1[3]. This is equivalent to the Longest Common Subsequence (LCS) (Elzinga, 2008; Studer & Ritschard, 2016). We chose this because we are primarily concerned with the length of NEET spells for which the classical optimal matching is a reasonable choice (Studer & Ritschard, 2016) and because we do not have any theoretical reasons to assume different costs (cf. Brzinsky-Fay, 2007; Brzinsky-Fay & Solga, 2016). These costs quantify how many changes would need to be made to one sequence in order for two

[3]We have also used two other cost setting structures, OMspell and SVRspell (see Studer & Ritschard, 2016). Both do not give clear results as described in Table A.2.1 in the Appendix.

sequences to be equal. We use the TraMinerR package for all steps related to the sequence analysis (Gabadinho et al., 2011). Then, we use hierarchical clustering with complete linkage to extract typologies of school-to-work trajectories. We do so after consideration of Ward's and average linkage (see Appendix A.2). While Ward's algorithm is the most commonly used clustering algorithm in sequence analysis applications, we opted for complete linkage because it gave us a clear NEET cluster and a clear school-to-work cluster. Other linkage functions such as centroid or single linkage split the data in one large group and one single observation which is the most different from the rest. This is not useful for our application.

We align sequences on the first non-education state observed since January 2001. We then exclude the month of August in every year of observation to exclude seasonal regularities in the data that are related to the summer break between school years. During August, some pupils change schools and thus are not registered consecutively in education. The economic or educational activity in August is therefore not easy to interpret and would likely result in faulty interpretations of school-leaving. We also exclude sequences that have missing states for more than 10% of the observations as mentioned in the data section.

For our main analyses we use the two cluster solution. This solution was selected after careful inspection of the following cluster solutions (see Appendix A.2).

Note that we do not claim that this solution is the right cluster solution, because, as is the nature of hierarchical clustering, there is no one *right* solution (Warren et al., 2015). In fact, there are as many cluster solutions possible as there are data points. Still, we do claim that our chosen solution is the most useful one as it is the most relevant and parsimonious typology to answer our research question[4].

Figure 3.1 displays the two main typologies, which can easily be described as successful and unsuccessful school-to-work transitions. The first trajectory mainly represents the classical school-to-work transition for youth who follow vocational training or higher education and then find employment. The second cluster ends with the majority of young people being NEET twelve years after leaving secondary school. Though some trajectories start in education, especially vocational training, or work, around 80% are NEET in the end. In Table 3.3, we show average marginal effects from logistic regression models to explain these patterns. Similar patterns also emerge when we take another clustering algorithm, Ward's or average linkage

[4]Compared to **Chapter 2** where, because of its exploratory perspective, we select a different cluster solution on similar data.

function. Or when we only keep young people with at least one month spent in NEET during the observation period.

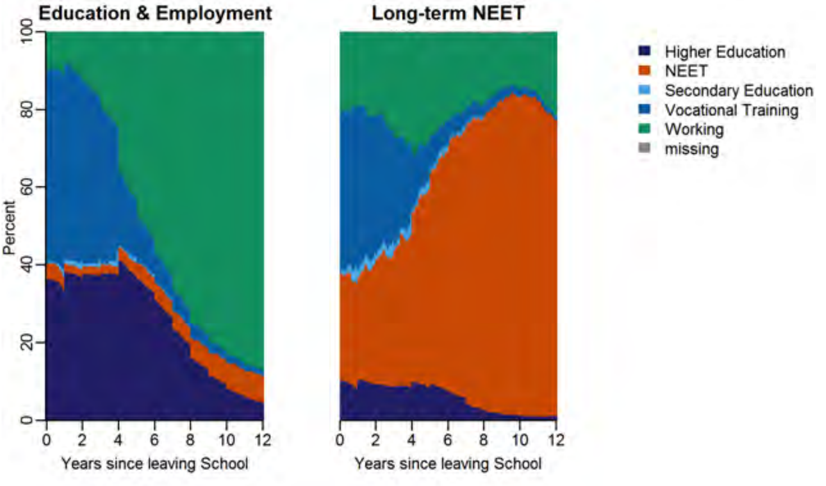


Figure 3.1: Status proportion plots of two main trajectory types. Source: Statistics Netherlands, own calculations.

3.5.2 Logistic regression

We use logistic regression to estimate the extent to which the probability to follow an unsuccessful school-to-work transition characterized by frequent, long-term periods as NEET, compared to the alternative pathway can be explained by social class (Model 1), human capital (Model 2), aspirational alignment (Model 3), and resilience (Model 4). Note that in all models, shown in Table 3.3, we control for the potential confounders, gender, immigration background, parental household structure, and age. As the dependent variable we take whether a young person follows the NEET trajectory or the standard school-to-work transition. We present average marginal effects. First, we report associations of the control variables. Young people who were not born in the Netherlands (AME = .019, $p < .01$) have a higher probability of following a long-term NEET trajectory than young people with two Dutch parents. The associations of immigration background hold over all four models. Also, in all models, young women are more likely to become long-term NEET than young men (AME = .020, $p < .001$). The household status variable is not significant in any model. Age is related to a higher probability to become NEET as well (AME = .008, $p < .001$).

Model 1 shows that social class is negatively associated with following a long-term NEET trajectory. Having lower educated parents is associated with a higher probability of their children to become long-term NEET compared to having parents with at least secondary education (AME = .023, $p < .001$). University educated parents reduce the likelihood to become NEET (AME = -.016, $p < .01$) compared to parents with secondary education. Once we add the human capital measures in Model 2, parental education becomes insignificant, indicating the theorized mediation via education. Short-term parental joblessness does not change the probability to follow a long-term NEET trajectory. However, long-term parental joblessness is significantly correlated with a higher probability to follow a long-term NEET trajectory (AME = .029, $p < .001$). This association is stable over all four models. Living in rented housing compared to owned housing is also correlated with a higher probability to become long-term NEET (AME = .044, $p < .001$). A one percent increase in parental household income is correlated with a decrease in the probability to become long-term NEET by half a percent (AME = -.005, $p < .05$). However, this association does not hold in later models. Based on Model 1 we can accept Hypothesis 1 which predicted that a higher social class background lowers the risk to become NEET.

Table 3.3: Logistic regression models, average marginal effects and standard errors shown.

	Model 1	Model 2	Model 3	Model 4
Social Class				
Parental education, ref. cat.: Secondary				
Lower	0.023***	0.007	0.007	0.008
	0.006	0.005	0.005	0.005
Tertiary	−0.016**	−0.003	−0.004	−0.004
	0.005	0.006	0.006	0.006
Parental unemployment history, ref. cat.: Never				
1 to 2 years	0.008	0.006	0.006	0.005
	0.005	0.005	0.005	0.005
more than 2 years	0.029***	0.024***	0.024***	0.023***
	0.006	0.006	0.006	0.006
Household ownership, ref. cat.: Owned				
Rented	0.044***	0.029***	0.028***	0.028***
	0.006	0.006	0.006	0.006
Parental household income, log	−0.005*	−0.003	−0.003	−0.003
	0.002	0.002	0.002	0.002
Human Capital				
Education (last enrolled), ref. cat.: VMBO				
Practical		0.067***	0.067***	0.066***
		0.013	0.013	0.013
HAVO		−0.053***	−0.054***	−0.053***
		0.008	0.008	0.008
VWO		−0.063***	−0.064***	−0.063***
		0.009	0.009	0.009
Other (assigned)		0.097***	0.098***	0.098***
		0.014	0.014	0.014
Cognitive skills (SD)		−0.000	−0.001	−0.001
		0.003	0.003	0.003
Aspirations				
Occupational aspiration, ref. cat.: I. Aligned (High)				
II. Misaligned (Over)			−0.007	−0.008
			0.011	0.011
III. Academic uncertain			−0.007	−0.008
			0.009	0.009

Continued on next page

Table 3.3 – continued from previous page

	Model 1	Model 2	Model 3	Model 4
IV. Misaligned (Under)			−0.015	−0.016
			0.018	0.018
V. Aligned (Low)			−0.003	−0.004
			0.011	0.012
VI. Vocational uncertain			−0.012	−0.014
			0.011	0.011
VII. Uncertain professional			0.004	0.004
			0.012	0.012
VIII. Uncertain nonprofessional			−0.014	−0.015
			0.009	0.009
IX. Orientation less			−0.014	−0.015
			0.008	0.008
Personality				
Resilience type, ref. cat.: Non-Resilient				
Resilient				−0.036***
				0.007
Controls				
Gender, ref. cat.: Male				
Female	0.020***	0.027***	0.027***	0.027***
	0.004	0.004	0.004	0.004
Age	0.008***	0.030***	0.029***	0.030***
	0.002	0.003	0.003	0.003
Household status, ref. cat.: Two parents				
Single parent	0.012	0.007	0.007	0.006
	0.008	0.007	0.007	0.007
Caretaker	0.047	0.020	0.021	0.020
	0.030	0.023	0.023	0.023
Immigration background, ref. cat.: Dutch				
First generation	0.020	0.013	0.011	0.012
	0.012	0.011	0.011	0.011
Second generation	0.019**	0.021**	0.020**	0.020**
	0.007	0.007	0.007	0.007
Observations	10,955	10,955	10,955	10,955
Pseudo R^2	0.074	0.138	0.139	0.143

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Statistics Netherlands, own calculations.

Model 2 adds measures of human capital. Compared to those who followed the vocational track, those from the general tracks are significantly less likely to follow a NEET trajectory (AME (HAVO) = -.053, $p < .001$; AME (VWO) = -.063, $p < .001$). Practical education increases the probability to become long-term NEET compared to VMBO (AME = .067, $p < .001$). Education with the label “Other (assigned)” is also significantly related to a long-term NEET trajectory (AME = .097, $p < .001$). Note also that age is now more strongly correlated with becoming NEET. Before including education in the model, the correlation of age was likely suppressed because the general tracks take longer to finish and also offer better labor market prospects. Now that education is included, age more likely represents grade retention and thus is a proxy for human capital as well. All in all, this supports Hypothesis 2a. However, Model 2 also shows that in addition to the educational track, cognitive skills do not add to the explanation of becoming a long-term NEET, which refutes Hypothesis 2b.

Model 3 adds the measure of aspirational alignment. The reference category represents young people who aspired to a professional occupation and followed the general education track. Compared to them, there are no significant differences in the probabilities to become NEET for pupils with misaligned or uncertain aspirations. This does not provide support for the Hypothesis 3a that uncertainty would put a pupil at a higher risk to become long-term NEET. There is also no evidence to accept Hypothesis 3b, because misaligned occupational aspirations do not increase the likelihood to become NEET.

In Model 4 we add the measure of resilient personality. The likelihood of following a NEET trajectory does indeed change to the favor of young people with a resilient personality (AME = -0.036, $p < .01$). Thus, we can accept Hypothesis 4, because young people with resilient personalities are less likely to become NEET than those with a non-resilient personality.

In addition to the direct association of social class and NEET, we hypothesized that social class would be mediated through education, resilience, and aspirational alignment. In Table 4 we show the results from the KHB decomposition analysis. The columns show the mediators (z-variables) education, resilience, and aspirational alignment. For education, we see that 24.98% of the total association of lower social class background are due to the educational track pupils are sorted in. For resilient personality and aspirational alignment, mediation is negligible with 1.15% and 1.68%. Thus, we can accept Hypothesis 5a but not Hypotheses 5b and 5c.

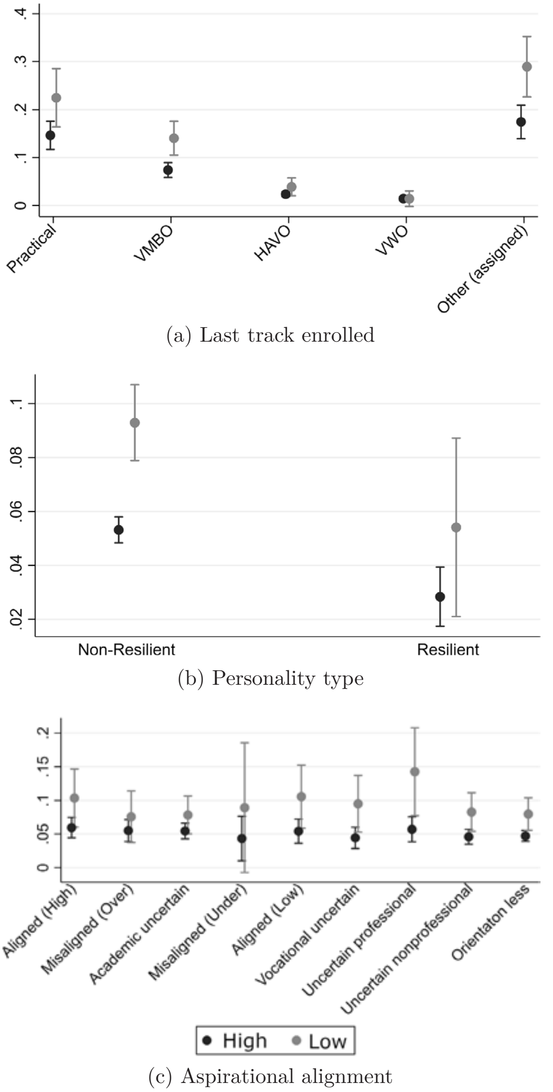
We also modelled the moderation of social class by pupil’s education, personality, and aspirations. To aid interpretation, we computed a binary indicator of low socioeconomic status which we will interact with the variables

Table 3.4: Decomposition of total, direct, and indirect associations (log odds) of parental education and NEET risk

	Indirect (Z-variable)		
Lower social class background (0/1)	Education	Resilient personality	Aspirational alignment
Total (Reduced)	1.320***	1.306***	1.299***
Direct (Full)	0.990***	1.291***	1.277***
Indirect (Diff)	0.330***	0.015	0.022**
Percent due to Indirect:	24.98%	1.15%	1.68%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Statistics Netherlands, own calculations.

of interest. We define lower socioeconomic status as below median household income, living in rental housing, having been jobless at least once and not having a university education. In Figure 3.2, we show three panels of figures, each showing one set of interactions. Panel A shows the predicted probabilities for youth to become NEET on the y-axis depending on their education (x-axis) and their parental social class (dot markers). We see that for youth who followed HAVO or VWO a low social class background (Low SES = Yes) does not make a significant difference to the probabilities to become long-term NEET as compared to not having a low socioeconomic background. However, for VMBO, or other education, the negative effect of low social class is increased. In other words, for low educated youth, coming from a high social class serves as a protector. We conclude that Hypothesis 6a is accepted: social class is being moderated by education.



(a) Last track enrolled

(b) Personality type

(c) Aspirational alignment

Figure 3.2: Predicted probabilities to become long-term NEET by education, personality, and aspirational alignment and levels of parental socioeconomic status. Source: Statistics Netherlands, own calculations.

In Panel B we see that a lower social class increases the probability to become NEET significantly for non-resilient youth compared to non-resilient youth without a low social class background. We also see that for resilient youth, there is no significant differences to become NEET. This means that social class is moderated by youth's resilience, and we therefore accept Hypothesis 6b.

Panel C shows that the effect of lower social class for the most part does not significantly vary over the different levels of aspirational alignment. However, for the uncertain categories (vocational uncertain, uncertain professional, uncertain non-professional, orientation less), the risk of becoming NEET is slightly elevated for those with a lower social class background, although the difference is on the borderline of significance. We conclude that we cannot accept Hypothesis 6c.

3.6 Conclusion

We set out to answer why some young people in the Netherlands become NEET and others successfully transition from school to work. More specifically, we asked to what extent and how human capital, social class, occupational aspirations, and personality predict a school-to-work trajectory that is predominantly characterized by time spent in NEET. Our findings have implications for ongoing research and debates about young people who are NEET – who they are, and how to prevent them from becoming NEET. The sequence analysis shows that many NEET trajectories begin at an early age, often after early-school leaving. Many of these are characterized by long-term disengagement and possible path-dependency. We also show that parental education is partially mediated through young people's education, but that there are considerable direct effects of parental education as well as other social background measures, such as parental joblessness and immigration background. Hence, we subscribe to an interpretation of young people who are NEET to be subjected to multiple risk factors. One important factor is certainly early school-leaving. In an occupationally structured labor market such as the Netherlands, young people without any type of credentials will face more set-backs during the school to work transition (de Lange et al., 2014).

Unlike previous research (Sabates et al., 2011; Staff et al., 2010; Yates et al., 2011) we did not find strong evidence that youth who had uncertain or misaligned occupational aspirations are more likely to follow long-term NEET trajectories, although uncertain aspirations seem to matter more for low SES youth. The fact that we find no strong results could be explained by the highly stratified educational system of the Netherlands in which pupils do not need to have clear plans because for the most part they are streaming through whatever trajectory they were assigned to. Most research on uncertain and misaligned aspirations was focused on education systems without extensive tracking such as the US (Staff et al., 2010) or the UK (Yates et al., 2011). It might also be because our data measured aspirations at age 12, which may have been too early. The two mentioned studies have data measured at age 16.

We also investigated the role of personality. We found that a resilient personality partly protects youth against becoming long-term NEET. Moreover, we find that being resilient decreases the NEET risk more strongly for low SES youth than for high SES youth. Not being resilient has a stronger negative impact for youth from lower class background than for youth from higher social class backgrounds. Resilience is thus a key asset, especially for lower social class youth. In addition, the protecting effect of resilience we find is about the same size as the effect for growing up in rented housing or having long-term jobless parents. Hence, if youth, especially low social class youth, have such resilient personality traits, they have a better chance to not become long-term NEET.

Also, future research should further disentangle the identified trajectories. Sequence analysis has proven to be a useful tool to make sense of the manifold of school-to-work trajectories. Yet it might be worthwhile to focus more on vulnerable subgroups such as young women or children of immigrants. Finally, cross-national comparisons are needed to provide us with evidence of the role of institutions.

Chapter 4

Automation Risks of Vocational Training Programs and Early Careers in the Netherlands[1]

4.1 Introduction

Technological innovations have long been thought to play a crucial role in driving social inequalities. Yet, the way recent innovations in robotics and artificial intelligence may affect future social inequalities is still poorly understood. Some evidence suggests that the widespread adoption of automation technologies has increased employment and income polarization by particularly affecting tasks performed in medium-skilled-medium-income jobs (Autor, 2015; Autor et al., 2003; Autor et al., 2008; Goos et al., 2014, 2009; Spitz-Oener, 2006). Other studies argued that such routine-biased polarization is not a given and show that it has not taken place to the same extent in different European countries, especially compared to the US (Fernández-Macías & Hurley, 2016; Fouarge, 2017; Oesch & Piccitto, 2019). One explanation is that recent developments in Europe are more driven by the cognitive task content of occupations (Fernández-Macías & Hurley, 2016) and therefore more in line with occupational upgrading (Oesch & Piccitto, 2019). If this is true, automating technologies driven by artificial intelligence – which may also be able to automate non-routine tasks – may affect social inequalities more strongly along these lines in the future. Some early evidence suggests this: wages in easier-to-automate jobs are lower (De

[1]This chapter was joint work with Annemarie Künn-Nelen, Raymond Montizaan and Mark Levels.

La Rica et al., 2020; Nedelkoska & Quintini, 2018), wages for abstract tasks have increased (Böhm, 2020; De La Rica et al., 2020), and reemployment probabilities for unemployed workers are lower if their previous occupation had a higher automation risk (Schmidpeter & Winter-Ebmer, 2021). However, much of this dynamic is still unclear.

In this study, we aim to gain insights in the way automation affects labor market inequalities by studying recent school-leavers from vocational education in the Netherlands. We take this approach for four reasons. First, most studies from the extensive literature on the labor-market consequences of technological change focus on macro-level data, for example on the job-level (e.g., Nedelkoska & Quintini, 2018). Few observe the micro-level processes that aggregate into these macro-level regularities. Second, we focus on young people's early careers because they are generally more volatile than careers of established employees. School-leavers are labor market outsiders and relatively unprotected by unions and collective employment protection agreements (Lindbeck & Snower, 2001). In times of uncertainty, they are likely the first to be fired and the last to be hired (e.g., Reagan, 1992) and more affected by labor market changes related to automation (see Dauth et al., 2021). For this reason, young workers can serve as the proverbial canary in the coal mine: we expect that any observable impact of automation on workers will be first observed in this group. At the same time, the negative long-term effects of a failed school-to-work transition are well-studied (e.g., Bäckman & Nilsson, 2016; Gregg & Tominey, 2005; Mroz & Savage, 2006; Oreopoulos, 2007; Ralston et al., 2021; Steijn et al., 2006). This makes it crucial to understand how automation will impact school-to-work transitions, something we still know very little about. Hence, we will investigate how automation risks affect the school-to-work transitions (STWT) and early career.

Studying school-leavers helps us to better understand the role of education, and the possible consequences of being taught soon-to-be obsolete skills for the school-to-work transition and early careers. By their nature, education systems are relatively rigid and slow to respond to changing skill requirements. This is especially relevant in the case of vocational education and training (VET). However, there are three more reasons to focus on VET. First, the Dutch VET system not only differentiates based on ability, but also enforces that school-leavers hold at least a VET diploma to enter the labor market. As a result, graduates from VET generally transition to both lower- and middle-skilled jobs, making them well-suited to study processes of job polarization and educational upgrading. Second, VET is seen as a safety net for low-qualified youth (Iannelli & Raffe, 2007; Shavit & Müller, 2000). Technological change might erode this function, because automation is likely to first replace routine tasks (Goos et al., 2014). Some early evidence indeed suggests that VET graduates are particularly at risk to lose employment opportunities to automation (Ter Weel et al., 2021). Third, it is well established that in countries with a strong VET system, such as the Netherlands, VET graduates have an initial labor market advantage over graduates from general education (Breen, 2005; De Graaf & Ultee, 1998; Forster et al., 2016; Middeldorp et al., 2018; Ryan, 2001; Shavit & Müller, 1998; Wolbers, 2007). Yet, the specificity of their skills might also make them less able to respond to technological changes (Forster et al., 2016; Hanushek et al., 2017). Crucially, vocational specificity varies between VET programs (DiPrete et al., 2017; Forster & Bol, 2018; Mattijssen et al., 2022; Muja et al., 2019). Hence, some VET graduates might be less able to adjust to technological changes. By studying how automation risks of different VET level-field combinations are associated with the STWT and early-career wage growth, we aim to gain deeper insights in these dynamics.

Another aspect we want to raise here are compensation and exacerbation of risks. Some VET graduates might be more able to compensate for the negative effect of having graduated a VET program with a high automation risk. Social class, cognitive skills, and personality traits may compensate, but also exacerbate the effect that automation has on the STWT, thereby increasing social inequalities. For example, a higher social class background means access to more human, cultural, and social capital which should make VET graduates from higher social class backgrounds less affected by automation risks (cf. Bernardi & Gil-Hernández, 2021). VET graduates with higher cognitive skills might be more adaptable to automation because they are more likely to participate in further training (cf. Fouarge et al., 2013). The increased use of computers also boosted the demand for and the wages of people with better “people skills” (Borghans et al., 2014). Personality traits like openness to experience, entail a readiness to adapt and might be beneficial for individuals working in more easily automatable jobs. Neuroticism, on the other hand, entails negative reactions to changing environments (McCrae & John, 1992).

Our analyses answer the following research questions: *(1) To what extent and how are school-leavers from different vocational education and training programs exposed to automation risks, (2) to what extent does the automation risk of different VET programs correlate with early career paths and wage development of VET graduates during the school-to-work transition, and (3) to what extent does the correlation of automation on labor market outcomes vary by individual characteristics related to (a) social class, (b) psychological traits, and (c) cognitive skills?* To answer these questions, we use longitudinal register data of one cohort of VET graduates including information on diplomas, monthly employment status, and wages from Statistics Netherlands. These data allow us to follow the early career of VET graduates for 10 years. To the diplomas, we merge a range of indicators of automation risks. An advantage of this cohort is, that they were part of the Voortgezet Onderwijs Cohort Leerlingen (VOCL'99) study that includes data on cognitive skills and personality traits (Kuyper et al., 2003). We use sequence- and cluster analysis to group VET graduates by their type of STWT. We then use multinomial logistic regressions to test whether automation risk explains sorting into either trajectory. To test whether automation risk explains differences in wages and wage growth, we use random-effects growth curve models.

4.2 Background

4.2.1 Vocational education and automation

To understand how automation may alter the STWT of VET graduates, we start from the general argument that labor market allocation is a matching process between people and jobs. Matching and queuing theories (Logan, 1996; Spence, 1973; Thurow, 1975) presuppose that jobseekers and employers strive for optimal matches, given their preferences, opportunities, and constraints. Employers sort and match jobseekers into jobs based on observable characteristics, mainly educational credentials. These signal the extent to which candidates are immediately productive, i.e., do not require much additional training, and possess the required (although unobserved) skills for the given job. How strongly employers can rely on educational credentials differs between countries. In the Dutch case, the educational system is highly stratified and standardized and is characterized by strong institutional linkages and high vocational specificity (Bol & van de Werfhorst, 2013; Iannelli & Raffe, 2007; Raffe, 2008). In such a system, credential signals are clearer than in less standardized, less vocationally oriented countries (Müller, 2005). This is thought to help limit skill mismatches during the STWT (Levels et al., 2014) and to reduce training costs, making VET graduates more attractive to potential employers (Arum & Shavit, 1995; Barone & van de Werfhorst, 2011; Wolbers, 2007). Hence, VET graduates find jobs faster, are less often unemployed in their early career, and have a smoother STWT, even more so in vocationally oriented education systems (Breen, 2005; De Graaf & Ultee, 1998; Forster et al., 2016; Middeldorp et al., 2018; Ryan, 2001; Shavit & Müller, 1998; Wolbers, 2007).

However, this initial advantage might turn into a disadvantage making VET graduates less able to adjust to a changing labor market later in life (Forster et al., 2016; Hanushek et al., 2017). This argument also holds for differences between VET programs Bol et al. (2019). While mainly concerned with life cycle effects, we can apply this core logic to the STWT as well. Previously it was shown that the vocational specificity of programs is positively associated with employment chances in the early career (Muja et al., 2019). Automation adds a new aspect to this consideration.

Hence, the labor market success of VET graduates partly depends on the extent to which their skills are in demand, whether these skills make them immediately productive, and to what extent employers can infer information on these skills from educational credentials. However, the increased potential of automation technologies might change skill requirements and task composition of occupations (Autor et al., 2003; Brynjolfsson & McAfee, 2011). Therefore, it is important to know which occupations are most affected. Yet, quantifying the automation potential of occupations is not straight-forward. Frey & Osborne (2017) defined the automation risk of an occupation by judging which tasks machines cannot yet easily perform, i.e., perception and manipulation of complex objects as well as creative and social intelligence. Frey & Osborne (2017) estimated that 47% of US jobs are at risk of automation. Other studies arrived at similar conclusions. Bonin et al. (2015) estimate that share at 42% for Germany, using a task- rather than an occupational approach, whereas Dengler & Matthes (2018) estimate that share at 15%. Other findings are less alarming, for example 9% for the US (Arntz et al., 2016) or 14% for OECD countries (Nedelkoska & Quintini, 2018). However, all agree that automation will significantly change the labor market by destroying, creating, and altering jobs.

So, what does labor automation mean for VET graduates on the labor market? We expect that those who graduate a program that prepares for easier-to-automate occupations are less likely to have a successful STWT for two main reasons. First, because of the high standardization of VET and the tight institutional linkages (e.g., the SBB). Employers know which skills are taught in which VET program. Employers also form opinions about the future of certain jobs and the demand for certain skills and might thus infer the potential of automation technologies for each VET program. For example, in a survey with HR professionals in the Netherlands, two-thirds agreed that "Due to the use of robots and artificial intelligence, more jobs will disappear than new jobs will be created" (Somers & Fouarge, 2022). Employers might then sort educational credentials based on the perceived ease of automation (the potential return of investment) and then refrain from hiring graduates from VET programs that teach skills, which in their opinion will soon be obsolete.

The second reason why graduates from VET programs with higher automation risks might have less successful STWT is that labor market entrants are labor market outsiders (Lindbeck & Snower, 2001). Hence, they have yet to attain union protection, higher wages, and tenured contracts which protect already established employees. Meaning that in times of uncertainty, young employees, and labor market entrants are likely the first to be fired and the last to be hired (Reagan, 1992). If automation decreases the demand for easier-to-automate VET diplomas and shifts firms' investments from labor to capital, employers might resort to hiring stops rather than termination of existing employment. Therefore, we hypothesize that, *ceteris paribus*:

> *Hypothesis 1: The automation risk of occupations, which VET programs prepare for, is associated with unsuccessful STWTs that are characterized by long joblessness/NEET.*

However, automation risks might also lead to a different expectation. For some, as described above, automation likely means lower employment chances or reduced earnings. Others, however, might react to this with continued learning and further education. Hence, we might also expect that, *ceteris paribus*:

> *Hypothesis 2: The automation risk of occupations, which VET programs prepare for, is associated with a higher probability to continue with education.*

Lastly, a similar, but less extreme reaction of employers than hiring stops would be to offer lower wages. Potential occupational downgrading, and the general lower demand for automatable skills lead us to expect that, *ceteris paribus*:

> *Hypothesis 3 & 4: The automation risk of occupations, which VET programs prepare for, is negatively associated with (H3) starting wages, and (H4) wage growth during the early career.*

4.2.2 The role of social class

While technological change may affect all of society equally, the resources to compensate for possible negative side effects are distributed unequally. Higher social class backgrounds mean access to more parental knowledge, resources, and networks, and cultural and social capital. Different theories of social mobility assume that parents from a higher social class background will mobilize their social, cultural, and economic resources to avoid their children's downward mobility and to secure advantages wherever possible (Bernardi & Gil-Hernández, 2021; Breen & Goldthorpe, 1997; Lucas, 2001). Higher social class families are likely better connected as well and can use their influence in their social network to find and secure a better labor market position for their children (Lin, 2001). Given the same situation, they can better assist their children in finding suitable employment. This leads us to expect that:

> *Hypothesis 5: the negative relation between automation risks and outcomes during the STWT is weaker for young people with a higher social class background.*

4.2.3 Moderation by cognitive skills

We expect that individuals with higher cognitive skills better adapt to new technologies. We base our expectation on the intuition that "cognition is essential in processing information, learning and in decision-making" (Borghans et al., 2008) and that lower educated workers are less likely to participate in further training (Bassanini et al., 2007; Fouarge et al., 2013). Additionally, workers whose jobs are the most likely to be substituted by machines are least likely to receive further training (Ehlert, 2020; Nedelkoska & Quintini, 2018). Those with higher cognitive skills, however, might be more able and willing to follow training. Hence, we expect that:

> *Hypothesis 6: The higher the cognitive skills of VET graduates, the weaker the expected effect of automation risk on their labor market outcomes.*

4.2.4 Moderation by personality

Personality traits offer another moderation mechanism of automation risks. These "relatively enduring patterns of thoughts, feelings, and behaviors that reflect the tendency to respond in certain ways under certain circumstances" (B. W. Roberts, 2009: 140) mean that individuals with different personalities will respond differently to automation risk.

Personality traits are commonly organized in five domains: extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience (Hendriks et al., 1999a; McCrae & John, 1992). However, we only hypothesize about the following three.

Conscientiousness describes people as being efficient and organized (McCrae & John, 1992). Conscientious people should cope better with technological changes because of their efficient and planful way of working. They likely plan ahead and thus avoid the negative effects of automation. Hence, we can expect that:

> *Hypothesis 7: The higher VET graduates score on conscientiousness, the weaker the expected association of automation risk on their labor market outcomes.*

People scoring low on emotional stability are described as anxious, self-defeating, and vulnerable (McCrae & John, 1992) whereas emotionally stable people "readily overcome setbacks" (Hendriks et al., 1999a). People scoring high on neuroticism might prefer positively affective, stable work environments that are predictable and frictionless (Bode et al., 2019). Technological changes at work disrupt this stability. Hence, we can expect that:

> *Hypothesis 8: The higher VET graduates score on emotional stability, the weaker is the expected association of automation risk and labor market outcomes.*

Openness to experience (autonomy) describes people as imaginative, curious, and following unusual thought processes (McCrae & John, 1992). Open individuals are therefore better equipped to adapt to novel situations or environments that provide opportunities to engage their intellectual capacities, such as new technologies. In our data, this trait is called autonomy. Autonomy correlates with openness to experience (Hendriks et al., 1999a). An autonomous person "can easily link facts together" and "thinks quickly" (Hendriks et al., 1999a). This adaptability might be beneficial in occupations with rapidly changing skill requirements and tasks. Hence, we hypothesize that:

> *Hypothesis 9: The higher VET graduates score on autonomy, the weaker is the expected association of automation risk and labor market outcomes.*

4.3 Data and methods

4.3.1 Data and sample selection

We use the same combination of survey and register data as in the previous chapter. Most importantly, the VOCL'99 survey includes personality traits, cognitive skills, and parental education, which are not available in register data. The register data on the other hand give us access to earned diplomas, socioeconomic activity over time, wages, employment contracts, and working hours. From the VOCL, we select first-time VET graduates who attained a MBO level 3 or 4 diploma between 2006 and 2012 (N = 5,588). The modal graduation year is 2007. To each diploma, we subsequently merge estimated automation risks which we will describe below.

For some variables from the VOCL survey, missing data is an issue. Most of the missing data stem from personality and cognitive ability items as well as the parental background questionnaire. Hence, we present the results for two samples. The first set of results retains all cases for which we have valid sequence, wage, and automation risk data. The second set of results includes personality traits, cognitive skills, and parental background variables, for which we proceed with listwise deletion. For the sequence analysis, we exclude observations with more than 10% missing states over the ten-year observation period, yielding a full sample of N = 5,222 and a reduced sample of N = 3,250. For the analysis of wages, the full sample is N = 5,471, the reduced sample is N = 3,393.

4.3.2 Operationalization

We use the following variables in our analyses. Descriptive statistics of all variables are presented in Table 4.1, histograms are provided in Appendix B.1.

Automation risk: We make use of two indicators of automation risks of occupations. One by Frey & Osborne (2017), and one by Somers & Fouarge (2022). The data by Frey & Osborne (2017) were originally estimated for occupations using the Standard Occupational Classification (SOC) 6-digit codes. We use the crosswalk provided by the US Bureau of Labor Statistics to merge these to ISCO 4-digit codes. Using data from the Dutch labor force surveys pooled over the years 2006-2008, we then calculate the weighted average of the automation risks of the most frequent 50% of ISCO 4-digit occupations within each VET level-field combination. The matching process is illustrated in Figure 4.1. By this, we construct a measure of automation risk for each VET level-field combination. The data by Frey & Osborne (2017) were first published in 2013 and aim to capture the extent to which automation, especially advances in machine learning, are expected to affect occupations in the near future. To do so, the authors, in cooperation with machine learning experts, hand-coded 70 occupations as automatable or not. They combine their ratings with task data from O*NET to train a classifying algorithm.

Table 4.1: Descriptive statistics in the first year after graduating MBO3/4

	Full sample			Reduced sample		
Variable	N	%/Mean	SD	N	%/Mean	SD
Automation risk (mean-split = 1)						
Frey & Osborne	2,633	52.69		3,250	46.43	
Somers & Fouarge	2,930	47.31		3,250	52.18	
Early career trajectory						
Employment	3,966	75.95		2,476	76.18	
Further Education	1,005	19.25		632	19.45	
MBO	90	1.72		54	1.66	
NEET	161	3.08		88	2.71	
Level of diploma						
MBO3	2,007	36.06		1,069	32.89	
MBO4	3,559	63.94		2,181	67.11	
Field of diploma						
Blue collar	1,256	22.57		730	22.46	
Services	4,310	77.43		2,520	77.54	
Occupational linkage	5,566	20.23	8.32	3,250	20.00	8.23
Migration background						
No	4,668	83.87		2,824	86.89	
Yes	898	16.13		426	13.11	
Gender						
Male	2,706	48.62		1,586	48.80	
Female	2,860	51.38		1,664	51.20	
Personality traits						
Autonomy				3,250	.36	.84
Agreeableness				3,250	1.64	1.10
Conscientiousness				3,250	.34	1.01
Extraversion				3,250	1.15	.86
Emotional stability				3,250	1.02	.90
Cognitive skills				3,250	33.56	8.63
Parental homeownership						
Owned				2,317	71.29	
Rented				933	28.71	
Parental Education						
Lower				894	27.51	
Secondary				1,654	50.89	
Tertiary				702	21.60	
Parental household income				3,250	40,481.29	16761.45
N (Persons)	5,566			3,250		

Source: Statistics Netherlands, own calculations.

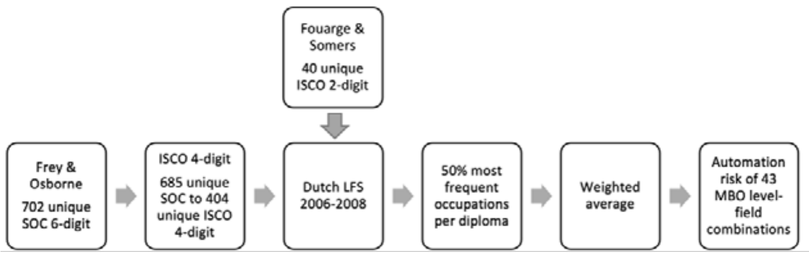


Figure 4.1: Matching logic of automation risk to VET programs.

As the data by Frey & Osborne are primarily informative for the American labor market, we also use data by Somers & Fouarge (2022) which are based on an expert survey of Dutch human resource professionals. In it, participants were asked to give their opinion on the likelihood that employees will spend more or less time on certain tasks in the future. We use the share of tasks within each occupation on which employees are expected to spend less time as an indicator of automation risk.

The calculated average automation risk for each level-field combination is shown in Figure 4.2. To better compare the values between the two, we have sorted the level-fields in ascending order by the Frey & Osborne indicator. The lowest automation risk is found in health and care related fields. In that, the two measure mostly agree. One noteworthy outlier in the upper third are ICT related fields. Here, the S&F indicator, based on Dutch expert's survey, deviates from the expectations by the two other indicators. This might be due to idiosyncrasies of the Dutch labor market that F&O, based on an American occupational structure, is not picking up. The middle section is dominated by jobs with mostly manual tasks, such as construction, mechanical engineering, electrical installation, logistics, bakery, and horticulture and agriculture. Both F&O and S&F foresee a higher risk for tasks in these occupations to be automated and spent less time on. Lastly, the fields with the highest automation risk prepare for occupations with mostly routine-cognitive tasks, like secretarial and administrative work.

Occupational linkage: For each VET level-field combination, we calculate the share of employees in the most common occupation-education combination from all possible combinations within one level-field combination. For example, in the MBO3 level-field ONR23213 horticulture and green care, 54% of graduates in 2006 and 2008 work in ISCO2008-code 6113 Gardeners, horticultural and nursery growers. Hence, the occupational linkage of that program is 54%.

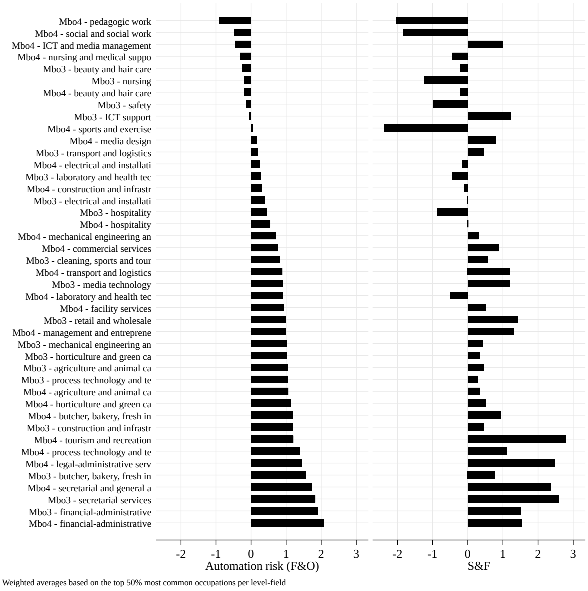


Figure 4.2: Automation risks of vocational education and training level-field combinations. Source: Own calculations based on Frey & Osborne (2017), Somers & Fouarge (2022).

Monthly activity sequence: Monthly activity is obtained by merging two datasets from the Dutch register data (Bakker et al., 2014). The first includes data on the main economic activity based on the main source of income. The original variable has twelve states. We combine the four states *employee*, *director/major shareholder*, *self-employed*, and *other self-employed* into *working,* the six states *recipient of unemployment insurance, recipient of welfare, recipient of other social benefits, recipient of illness and disability benefits, recipient of pension* and *other without income* into *NEET,* and the two states (*not yet) pupil/student with income* and (*not yet) pupil/student without income*, into *Education.* To capture employment changes, we separate *Working* into *Working A* and *Working B.* The first employment spell after leaving VET will receive the state *Working A*, the following employment spell will be *B*, the third *A*, the fourth again *B* and so on. This is necessary as without it, employment spells of multiple years would be indistinguishable from many different employment spells within the same time. The second dataset includes registrations in publicly funded education to distinguish secondary education from further education. We merge the two variables, whereas education overwrites other states. Primary education, practical education, and secondary education are grouped together as *Secondary Education and below*. The other states represent the three main types of further education in the Netherlands, *upper secondary vocational education (MBO), university of applied science (HBO),* and *university (WO).*

Log hourly wage: We calculate the hourly wage from the Dutch register data on wages and working hours of different contracts per month, sum up all contracts per person-month, divide the wage by four weeks and by working hours per week. Negative values, hourly wages lower than the minimum wage for 19-year-olds in 2006 (€3.86), and hourly wages higher than three standard deviations above the mean are coded as missing[2]. We deflate these nominal wages to real wages by dividing them by their corresponding yearly customer price index (2015 = 100). The resulting variable has a mode of €15.51 and a standard deviation of €4.95. We use the natural logarithm of that variable in our analysis.

Cognitive skills: The VOCL'99 study included a test of cognitive skills in three domains, math (Cronbach's $\alpha = .83$), language (Cronbach's $\alpha = .74$), and information processing (Cronbach's $\alpha = .79$) (Kuyper et al., 2003). Values were imputed by CBS for students who only finished two of the three subdomains (Kuyper et al., 2003). No data is available for students who did not finish any subdomain (N = 1216) or only one (N = 36). The test is comparable to the test used to track pupils into general and vocational schooling tracks (CITO test), which was also included in the VOCL data, however with higher rates of missing data. Both tests correlate highly ($r = .82$, $p < .01$) and with the tracking advice ($r = .78$, $p < .01$; $r = .82$, $p < .01$). We standardize the score to the sample mean after listwise deletion.

Personality traits: We make use of the Five Factor Personality Inventory (FFPI) from VOCL'99 based on 100 items to measure the factors Extraversion, Agreeableness, Conscientiousness, Emotional Stability, and Autonomy. Responses were collected on a scale from 1 (not at all applicable) to 5 (entirely applicable). Observations were excluded if less than 70% of items were answered, responses were corrected for positive answering bias (acquiescence; 'yea-saying'), and missing values were imputed by the student's personal mean on the answered items per factor pole (Hendriks et

[2]According to Statistics Netherlands, negative income values may occur as administrative errors. For example, companies may use it to correct a previous administration error. Another source of negative income values is self-employment. A value of 0 can occur as unpaid vacation.

al., 1999b). To aid interpretation we standardize the scores to the sample means after listwise deletion.

Social class background: We measure social class background using several variables. First, we use the highest parental education from the VOCL'99 parent questionnaire. We distinguish tertiary, secondary, and lower education. In addition, we use the yearly household income from Dutch register data. We use the value from 2003 as it is the earliest available. Some observations have negative values that we replace with €1. We mean center the variable to ease interpretation of interaction terms. We also use information on the dwelling status of the parents from Dutch register data and distinguish between owned and rented housing.

MBO Level: From the education registers, we distinguish MBO Level 3 from Level 4 and code them as a binary variable.

Field of Education: We separate educational programs into service- and blue-collar-orientated programs and consider the fields *Education*, *Humanities and Arts*, *Social Sciences, Business and Law*, *Science, Mathematics and Computing*, *Health and Welfare*, and *Services* as Services and the remaining fields *Agriculture and Veterinary* and *Engineering, Manufacturing and Construction*, as blue-collar.

Gender: we use the variable provided in the register data to distinguish women (coded as 1) from men (coded as 0).

Immigration background: We distinguish pupils with two Dutch-born parents (coded as 0) from pupils who with at least one foreign born parent or who themselves were not born in the Netherlands (coded as 1).

4.3.3 Sequence analysis

We use sequence analysis to explore early career trajectories from the month of VET graduation until ten years after and use optimal matching to calculate a pairwise measure of dissimilarity given a pre-defined cost structure with insertion/deletion costs set as 2 and substitution costs set as 1. This is equivalent to the Longest Common Subsequence (LCS)[3] (Studer & Ritschard, 2016). We chose this because we are primarily concerned with the length of NEET spells for which the classical optimal matching is a reasonable choice (Studer & Ritschard, 2016). We use the TraMinerR package for data preparation and calculation of the distance matrix (Gabadinho et al., 2011) and the WeightedCluster package for steps related to clustering

[3]Two other cost-setting regimes, OMspell, and SVRspell do not yield any useful partitions. OMspell yields a partition consisting of very similar, very heterogenous clusters. SVRspell yields clusters containing single cases.

(Studer, 2013). We use four common clustering algorithms, Ward's, average, complete, and partition around the medoid (PAM). Cluster quality indicators are presented in the Appendix B.2.1. We rank the most common quality indicators for each clustering method to assist us in choosing one cluster partition to present. Partitions using the average linkage algorithm rank highest in cluster qualities but produce clusters containing less than ten cases, making them unsuitable for further analyses. Hence, we settle for the four-cluster partition using the complete linkage algorithm. To get an overview of how clusters partition with the hierarchical methods, cluster trees of Ward's algorithm and complete linkage are available in Appendix B.2.1[4].

4.3.4 Models

After selecting a cluster partition, we model the probability to follow a specific trajectory using multinomial logistic regression. The basic specification can be written as follows, where the log odds of following trajectory k compared to the reference category K, depend on automation risk and a battery X of covariates:

$$ln\left(\frac{P(Cluster_i = k)}{P(Cluster_i = K)}\right) = \beta_k + \beta_k AUTORISK_i + \beta_k X_i, for\ k = 1, ..., K \tag{4.1}$$

In addition to the STWT, we expect automation risk to be associated with wages and the wage growth in the early career and test these hypotheses using growth curve models (GCM) as described in Rabe-Hesketh & Skrondal (2008). GCM are two-level multilevel models. In this case, multiple time-observations (level 1) are nested within individuals (level 2). This allows us to estimate differences in wage growth between individuals and intra-individual differences in wage growth over time. In our case, the main variable of interest is the estimated automation risk of a VET level-field combination AUTORISK. As AUTORISK is an attribute of a VET level-field combination, we cluster the standard errors on a level-field basis. The basic specification can be written as:

$$y_{it} = \beta_0 + \beta_1 YEARS_{ti} + \beta_2 AUTORISK_i + (\mu_{0i} + \mu_{1i} YEARS + \varepsilon_{ti}) \tag{4.2}$$

[4]The cluster tree for average linkage is not shown for data protection reasons because the clusters include less than ten cases.

Where the hourly wage y at time t for the individual i is regressed on a linear term for years since graduating VET and the time-invariant variable of the estimated automation risk of VET level-field combinations. The random part of the equation (in brackets) includes the random intercept (μ_{0i}), the random slope for linear time (μ_{1i}) and the person-specific residual error term (ε_{ti}). We build our models the following way. First, we begin with a null model to decompose between-individual and within-individual variances. We then add time since VET graduation in years to account for the average wage growth per year and add a random slope of time since VET to account for the different rates of wage growth per individual. We then add the indicators of automation risk of VET programs to the model. To test the hypotheses that automation risk is negatively associated with wage growth, we interact the automation risk variables with time since VET graduation. Lastly, we include variables to account for the educational differences within the VET system. First, the overall orientation of the VET program, either blue-collar or services. Second, the level, either MBO3 or MBO4. Third, the occupational specificity. Furthermore, we also include personality traits, cognitive ability, gender, immigration background, parental education, parental homeownership, and parental household income. We use Stata 16 (StataCorp, 2019) for all analyses besides the sequence analysis described above.

4.4 Results

4.4.1 Automation risk and school-to-work typologies

Results of the sequence analysis are shown in Figures 4.3 and 4.4. Figure 4.3 is a status proportion plot which shows the selected four clusters and their states over time. Figure 4.4 shows the transversal entropy for each cluster which quantifies how diverse a set of states is. A value of 0 means that all cases are in the same state, a value of 1 means that all cases are equally distributed over all states. It is transversal because for each month an entropy value is calculated and plotted over time, showing how and when the clusters are the most diverse in terms of states (Billari, 2001)

We extract four clusters representing typical trajectories after VET graduation in the Netherlands. Cluster 1, which we call *Employment* (75.9%, N = 3971), consists of cases that are working for most of the time. On average, 5.6 out of 120 months are spent in NEET. After initial stints in education, the transversal entropy falls to the lowest value of all clusters, signifying few transitions between states. Cluster 2 which we call *Further*

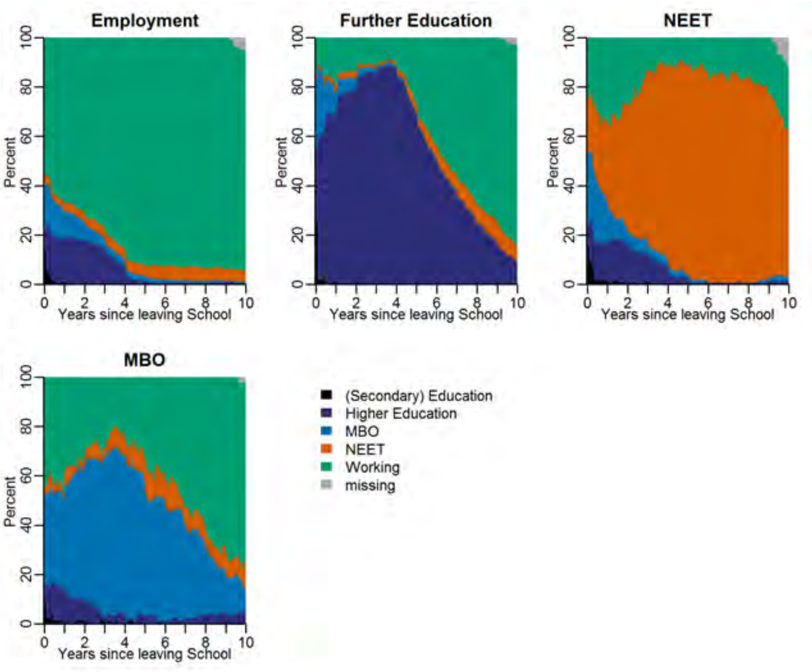


Figure 4.3: Status proportion plot of four typical post-VET trajectories. Source: Statistics Netherlands, own calculations.

Education (19.3%, N = 1010) represents a very common trajectory from MBO4 into HBO Bachelor programs. On average, 5.3 out of 120 months are spent in NEET. The transversal entropy of this cluster drops during four-year Bachelor programs and then increases as most make the transition into the labor market while others prolong their studies. Cluster 3 consists of 3% (N = 161) who follow a trajectory predominantly described by time spent neither in employment, nor in education (NEET). This cluster starts with a highly diverse set of states, shown by the very high entropy levels in the first two years. While some cases in this cluster move in and out of employment states, most of the time in this cluster is spent as NEET. On average, 82.3 out of 120 months are spent in NEET. Lastly, Cluster 4 shows a small group of 1.7% (N = 91) of MBO graduates who at some point re-enroll in a MBO program. On average, 8.7 out of 120 months are spent in NEET. We conclude that most graduates from MBO programs have a

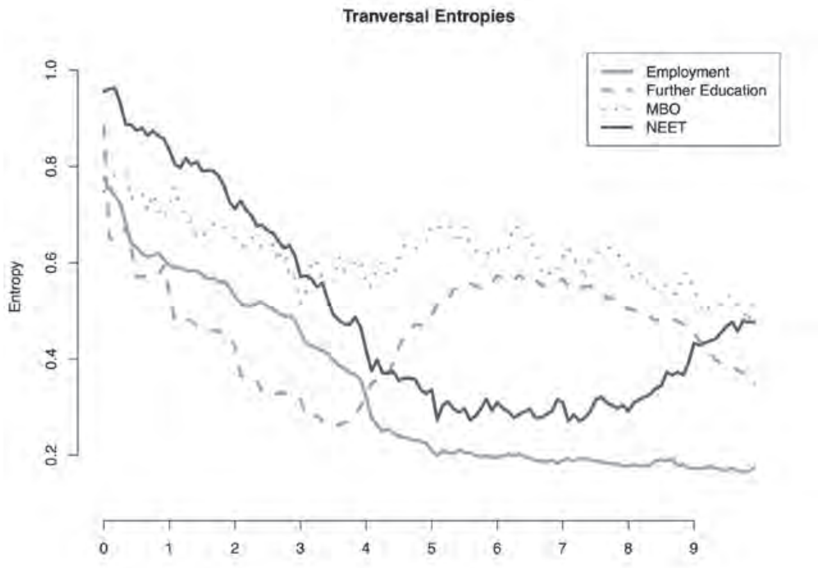


Figure 4.4: Transversal entropy plot for wach of the four post-VET trajectories. Source: Statistics Netherlands, own calculations.

successful school-to-work transition. Some continue with education, and only few follow a long-term NEET trajectory.

Figure 4.5 shows average marginal effects from the multinomial logistic regression of the probability to follow each trajectory. For the F&O indicator, we do not find any statistically significant associations with the trajectories. For the S&F indicator, however, we do find an increased risk to follow a long-term NEET trajectory relative to the reference category *Employment*. This would translate to an overall 1.4 percentage points higher probability of following a long-term NEET trajectory after graduating a high automation risk VET program compared to lower automation risk VET program. However, using terciles instead of mean-split dummies, we do not find this association[5]. In hypothesis H1, we expected that a higher automation risk would be associated with an increase in the probability to follow a NEET trajectory. We can confirm this, but only when using the S&F indicator (mean-split) based on the expectations of Dutch HR

[5]Results for other specifications can be found in Appendix B.4.

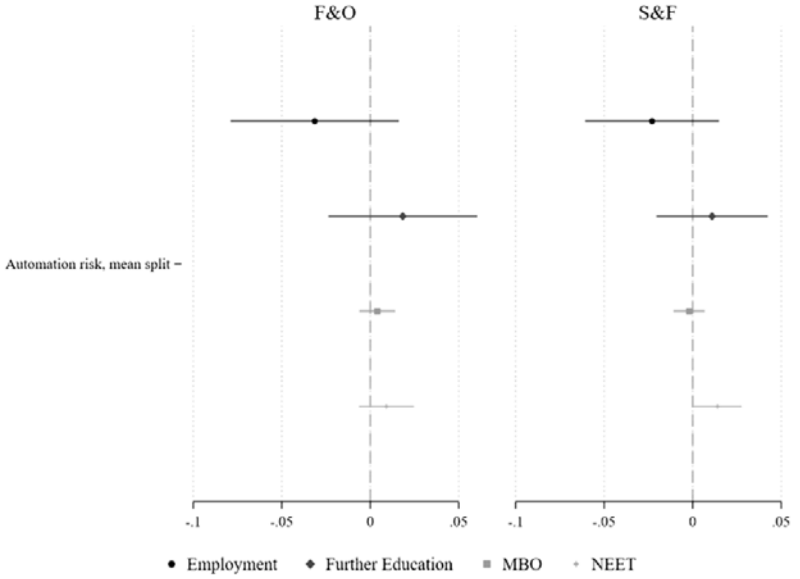


Figure 4.5: Average marginal effects to follow each early career trajectory for both indicators of automation risk of MBO programs. Controlled for occupational proportion, field, gender, migration background, MBO-level, personality traits, parental education, parental household income. Source: Statistics Netherlands, own calculations.

professionals and not when comparing terciles. Using the F&O indicator, we cannot confirm this expectation. We also cannot confirm hypothesis H2, in which we expected that automation risks would increase the probability to follow further education.

We also expected that cognitive skills, personality, and social class would moderate the association between automation risk and post-VET trajectories. Results for cognitive skills and personality are shown in Figure 4.6 (F&O) and 4.7 (S&F).

Results for the different social class indicators are shown in Figures 4.8 to 4.10 [6]. We find some statistically significant moderations, for example: a higher parental household income positively moderates the association of automation risk (measured as F&O mean-split, and S&F mean-split and

[6]Underlying tables of these results can be found in Appendix B.5.

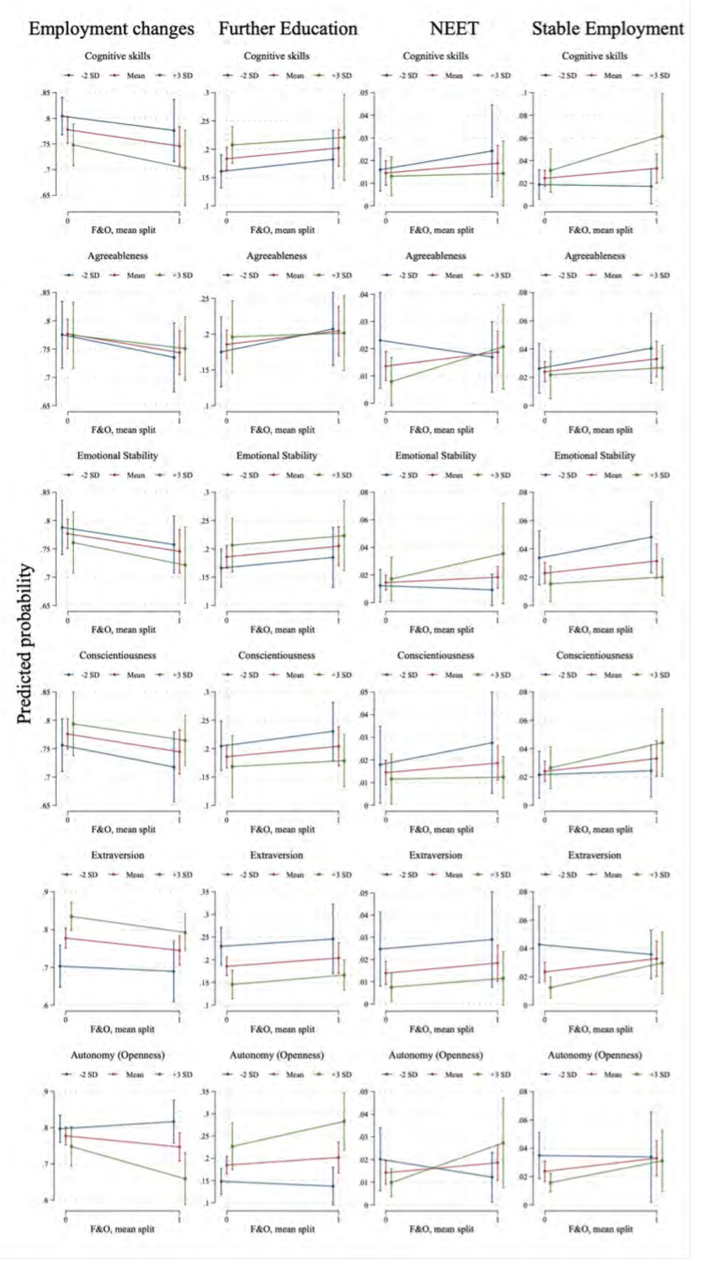


Figure 4.6: Predicted probabilities to follow one of four post-VET trajectories by automation risk (F&O) and levels of cognitive skills and personality traits. Source: Statistics Netherlands, own calculations.

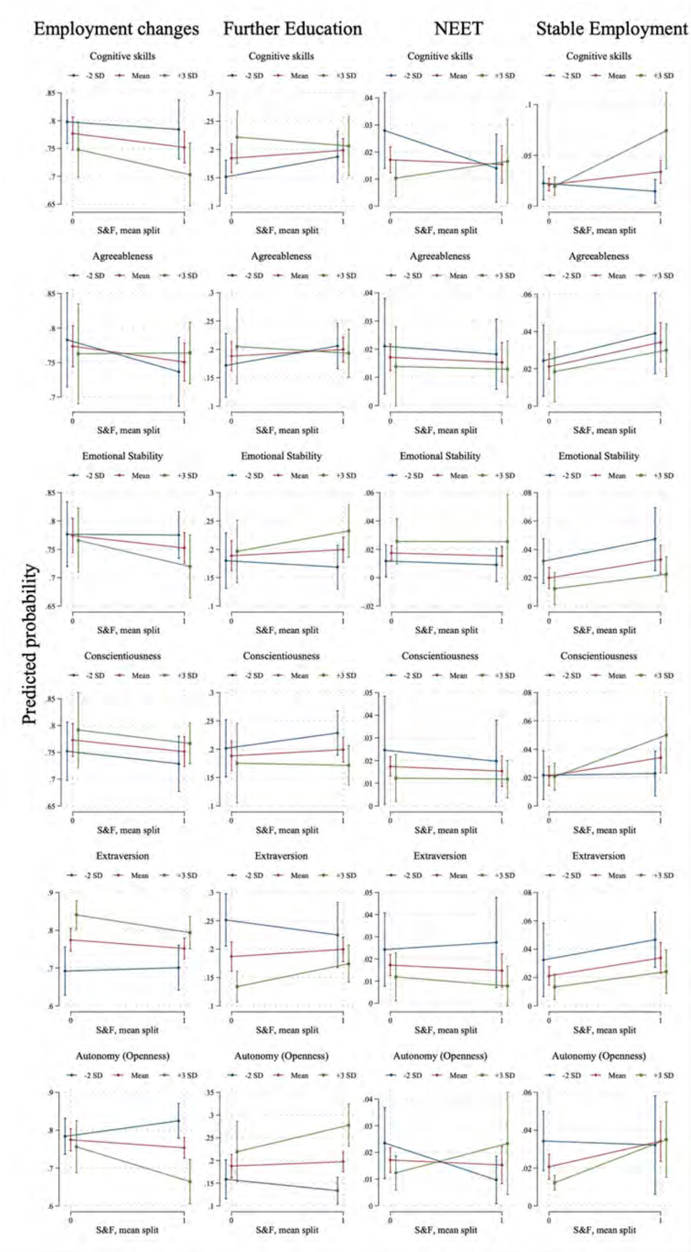


Figure 4.7: Predicted probabilities to follow one of four post-VET trajectories by automation risk (S&F) and levels of cognitive skills and personality traits. Source: Statistics Netherlands, own calculations.

high risk) when selecting into the continued MBO trajectory as opposed to the Employment trajectory. This is noteworthy because for graduates from MBO programs without a high automation risk, the association of parental household income is negative for the selection into continuing with MBO compared to selecting into the Employment trajectory. However, these moderations only hold with respect to the reference category (Employment) but not when considering overall predicted probabilities.

4.4.2 Automation risk and wage

Consistent with our expectations, Figure 4.11 shows that graduates from an easier-to-automate VET program have lower starting wages than VET graduates from programs with a lower automation risk.

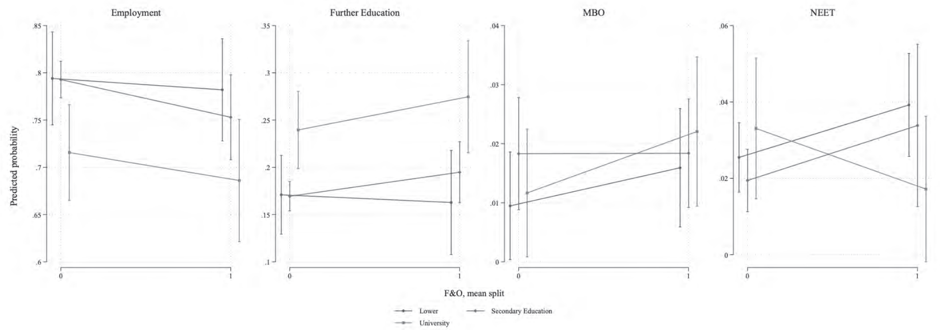
The null model GC0 without covariates decomposes the variance into between- and within-person variances (see Table B.6.1). The unexplained variance between individuals is .036. The unexplained variance within individuals is .035. The ratio of the between-variance and the sum of between and within-variance is the intraclass correlation, which is .507, meaning that for 50.7%, the differences in real hourly wages are due to differences between individuals and the remaining variation is due to differences within individuals.

In model GC1, we add a linear specification[7] of years since graduating from VET and a random slope of years (see Table B.6.1). The coefficient of years since VET is .038 and statistically significant at $p < .001$, meaning that on average, real hourly wages in the early career increase by 3.8% per year.

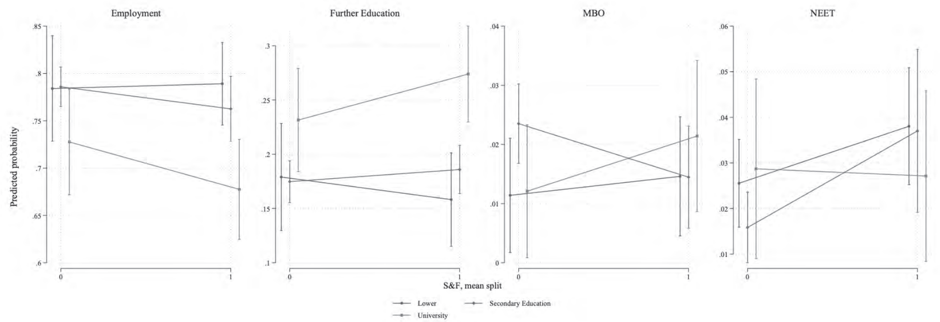
Figure 4.12 shows the results of the baseline models only including years since VET and either indicator of automation risk. We see that a higher-than-average automation risk (F&O) is associated with a decrease in hourly wages by 6.0% ($p < .001$) or 9.6% (S&F, $p < .001$). Once we control for the occupational linkage, i.e., how narrow the program prepares for one specific occupation, the association becomes less pronounced. Furthermore, once we adjust the standard errors for clustering in the 43 VET level-field combinations[8], most estimates substantially lose precision. In this

[7] Using year dummies does not lead to substantially different results. For the sake of interpretability, we prefer the linear form. Additional models are shown in the Appendix B.6.

[8] The results do not change substantially when excluding 3 level-field combinations that contain less than 10 individuals.

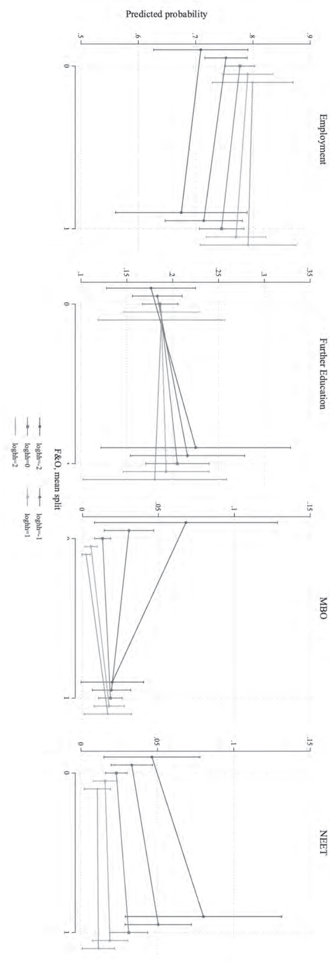


(a) Frey & Osborne

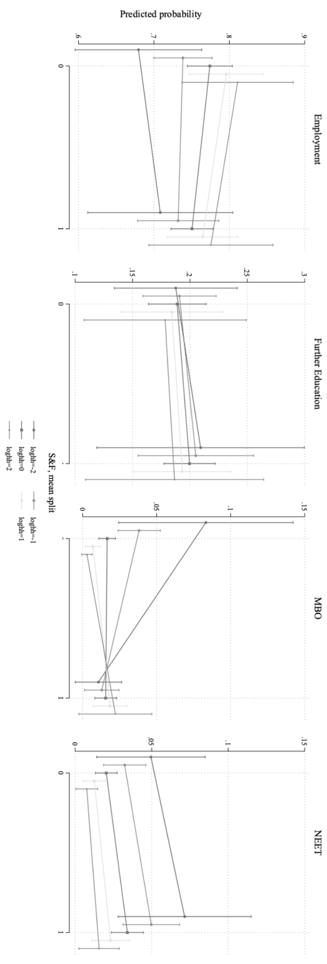


(b) Somers & Fouarge

Figure 4.8: Predicted probabilities to follow one of four post-VET trajectories by automation risk and parental education. Source: Statistics Netherlands, own calculations.

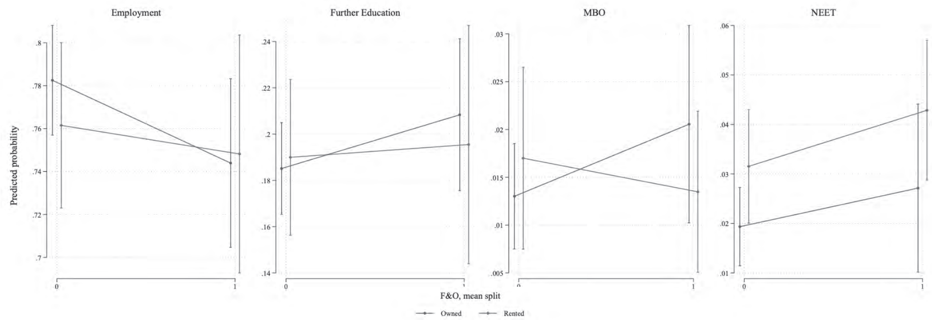


(a) Frey & Osborne

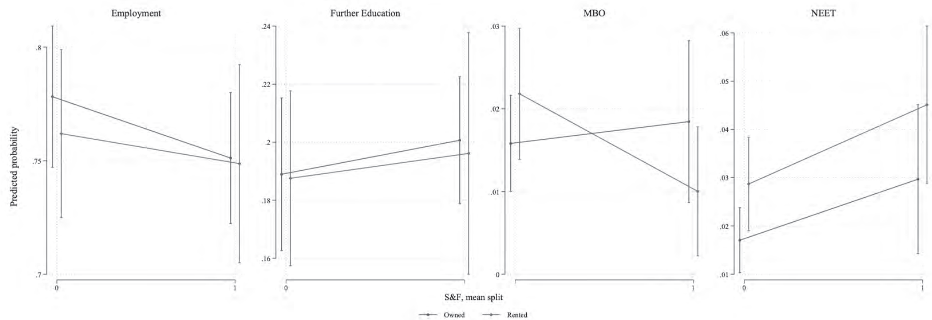


(b) Somers & Fouarge

Figure 4.9: Predicted probabilities to follow one of four post-VET trajectories by automation risk and parental household income. Source: Statistics Netherlands, own calculations.



(a) Frey & Osborne



(b) Somers & Fouarge

Figure 4.10: Predicted probabilities to follow one of four post-VET trajectories by automation risk and parental homeownership. Source: Statistics Netherlands, own calculations.

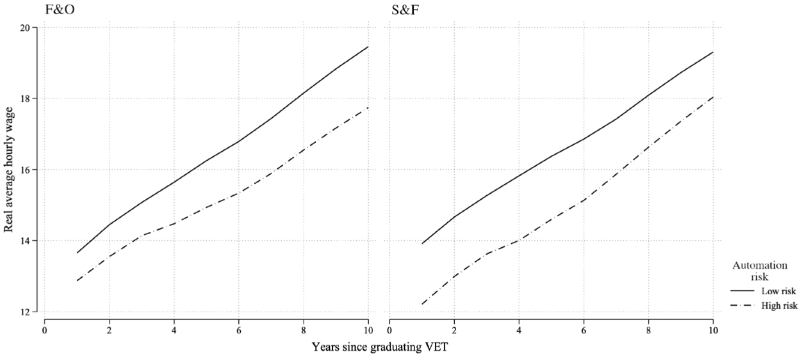


Figure 4.11: Average wage profiles of vocational education graduates by high and low risk of automation measured by two indicators (left: F&O, right: S&F). Source: Statistics Netherlands, own calculations.

specification only the S&F indicator remains statistically significant ($b = .088$, $p < .01$)[9].

Model GC2 (see Table 4.2) includes the interaction term of time (Years since VET) and automation risk to test whether wage growth varies with automation risk[10]. The coefficient of automation risk now relates to the association of automation risk with wages when the Years since VET variable is zero (= one year since graduation). Hence, in line Hypothesis 3, we can interpret this as a reduction in starting wages equal to 9.8 percentage-points for higher-than-average automation risk programs, using the S&F indicator automation risk ($p < .01$). For the F&O indicator we find a reduction of 5.0 percentage-points, although it is not statistically significant. Furthermore, we do not find that automation risk is negatively associated with wage growth. The interaction terms are close to zero and not statistically significant. The lack of statistically significant differences in wage growth might be explained

[9]Note that using the weighted average of all possible destination occupations instead of just the 50% most common ones yields significant coefficients for the F&O indicator. Generally, the results are more pronounced when using all possible destination occupations and less pronounced when only using the top 50% or even the single most common occupation. In addition, we investigated whether the results change when comparing terciles instead of mean-split-dummies. These reveal that the results are more pronounced for the highest tercile. For ease of interpretability, we present results using mean-split-dummies throughout the main analyses. See the Appendix for coefficient plots for different specifications.

[10]The results do not change substantially when using yearly dummies instead of a linear trend for time. See Appendix B.6 for coefficient plots.

Table 4.2: Random-effects growth curve models of log hourly wages on automation risk of VET programs.

	GC2	
DV: Real log hourly wage	F&O	S&F
Intercept	2.553***	2.588***
Years since VET	0.038***	0.036***
Automation risk, ref. cat. Low		
High	−0.046	−0.098**
High X Years since VET	−0.000	0.003
Occupational linkage	0.002	0.002
Variance components		
Between	0.046***	0.044***
Within	0.013***	0.013***
Random slope (Years)	0.001***	0.001***
Covariance intercept-slope	−0.003***	−0.003***
BIC	-45,311.41	-45,527.13
ICC	0.776	0.769
N (Person-years)	48,892	48,892
N (Persons)	5,471	5,471

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Statistics Netherlands, own calculations.

by collective agreements made on the sectoral level in which wage increases are mainly determined by largely fixed wage scales. So, with respect to wages, it seems that graduates from easier-to-automate VET programs are being hired for lower-paying jobs, but that differences in growth are not (yet) appearing. This is in line with results by (Cnossen et al., 2021) who also find differences in starting wage but now growth for different sets of skills learned in VET. In the following models, we therefore focus on differences in overall hourly wages and from now on will leave out the interaction term of automation risk and time.

We restrict Model GC3 to the reduced sample because the variables from the survey data include missing values. Compared to the estimates on the full sample the results do not change substantially. In Model GC4 we add several control variables. The results are shown in Table 4.3. After adding these, we control for the most common observable confounders, gender, social and immigration background, as well as personality and cognitive

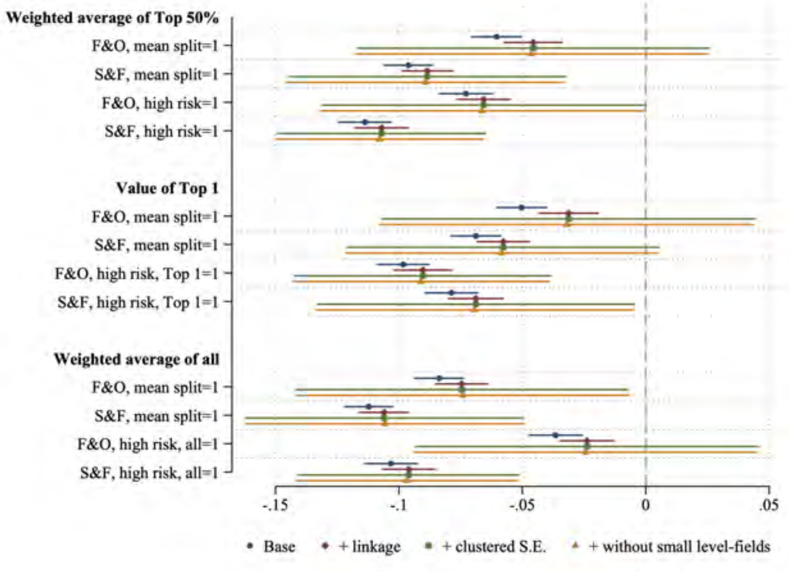


Figure 4.12: Coefficient plot of different model specifications of the association of automation risk and wages for different operationalizations of automation risk. Source: Statistics Netherlands, own calculations.

skills and properties VET programs. The result for the S&F indicator is largely stable to the inclusion of these variables. The result for the F&O indicator is now more pronounced (b = -0.065, $p < 0.05$). This is due to controlling for service orientation of VET programs as shown in Figure 4.13 [11]. Furthermore, we see that the difference between the high and middle tercile are now insignificant, (F&O: $\chi^2 = .06$, $p = .802$; S&F: $\chi^2 = .13$, $p = .719$). This implies that a substantial part of what we observe as a penalty for easier-to-automate VET programs might be interpreted as a premium for harder-to-automate VET programs compared to both medium and high-risk VET programs rather than a penalty for easier-to-automate VET programs.

Next, we investigate the hypothesized moderations of automation risk by cognitive skills and personality. We find statistically significant interactions for emotional stability (F&O), extraversion (F&O and S&F), and autonomy

[11] Additional figures in the Appendix illustrate a similar pattern for estimates using automation terciles.

Table 4.3: Random-effects growth curve models of log hourly wages on automation risk of VET programs.

	GC3		GC4	
DV: Real log hourly wage	F&O	S&F	F&O	S&F
Intercept	2.545***	2.571***	2.634***	2.622***
Years since VET	0.038***	0.038***	0.039***	0.039***
Automation risk, ref. cat. Low				
High	−0.042	−0.082**	−0.065*	−0.088***
Occupational linkage	0.002	0.002	0.002	0.002
Gender, ref.cat.: Male				
Female			−0.012	−0.031*
Immigration backgr., ref.cat. No				
Yes			−0.042***	−0.039***
Field of diploma, ref.cat.: Blue Collar				
Services			−0.071*	−0.047
Level, ref. cat.: MBO3				
MBO4			−0.002	0.004
Housing ownership, ref. cat. Owned				
Rented			−0.009	−0.007
Parental education, ref. cat. Low				
Secondary			−0.009	−0.008
Tertiary			−0.013	−0.012
Parental household income (log)			0.019+	0.019+
Variance components				
Between	0.046***	0.044***	0.045***	0.044***
Within	0.013***	0.013***	0.013***	0.013***
Random slope (Years)	0.001***	0.001***	0.001***	0.001***
Covariance intercept-slope	−0.523***	−0.521***	−0.541***	−0.545***
BIC	-28,694.3	-28,837.8	-28,679.5	-28,774.3
ICC	0.778	0.770	0.774	0.769
N (Person-years)	30,654	30,654	30,654	30,654
N (Persons)	3,393	3,393	3,393	3,393

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Statistics Netherlands, own calculations.

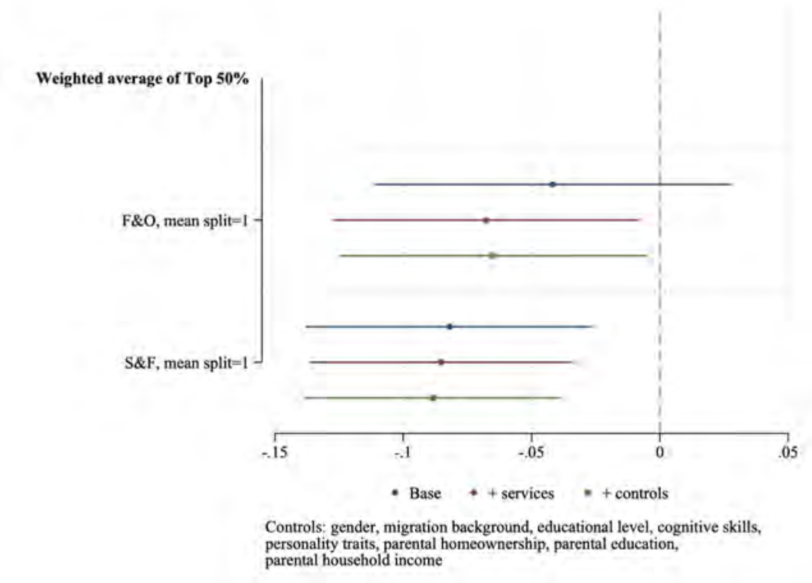


Figure 4.13: Coefficient plots of the association of automation risk (mean split dummy) and wages before and after including controls. Source: Statistics Netherlands, own calculations.

(F&O and S&F) [12]. The interactions are presented in Figure 4.14 and 4.15. In all plots we see the level effect of automation risk: lower automation risk VET programs (on the left) are associated with higher average wages than high automation risk VET programs (on the right). The different lines show how the association of automation risk and wage changes with different levels of cognitive skills and personality traits. For conscientiousness, we find no evidence of compensation (H7). For autonomy and emotional stability, we see that higher levels of these traits lead to slightly higher wages among higher risk VET programs. This is in line with the compensation mechanism in hypotheses H8 and H9.

Next, we move to the hypothesized moderations of automation risk by social class. While we do not find any evidence for compensation of automation risk by parental education (Figure 4.16) or parental homeownership (Figure 4.17), we find statistically significant interactions for parental house-

[12]Estimating either one joint model for all interactions or one model per interaction does not substantially change the results.

hold income (Figure 4.18): for those who grew up in high-income families, graduating from an easier-to-automate VET program is less penalizing for their wages.

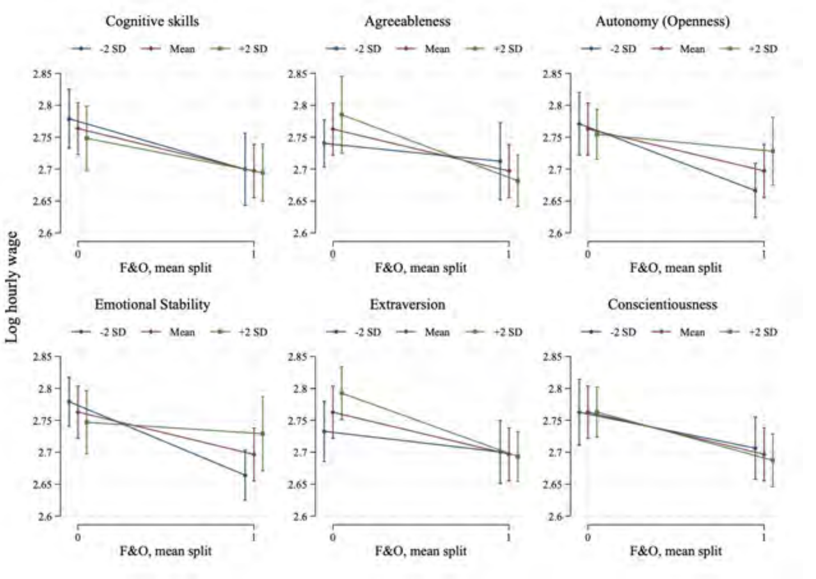


Figure 4.14: Coefficient plots of predicted log hourly wage by levels of automation risk (F&O) interacted with cognitive skills and personality traits. Source: Statistics Netherlands, own calculations.

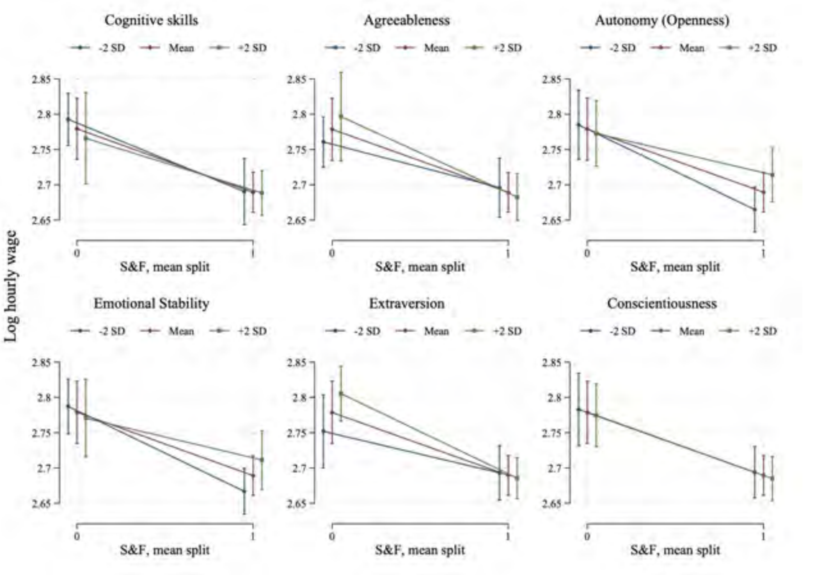


Figure 4.15: Coefficient plots of predicted log hourly wage by levels of automation risk (S&F) interacted with cognitive skills and personality traits. Source: Statistics Netherlands, own calculations.

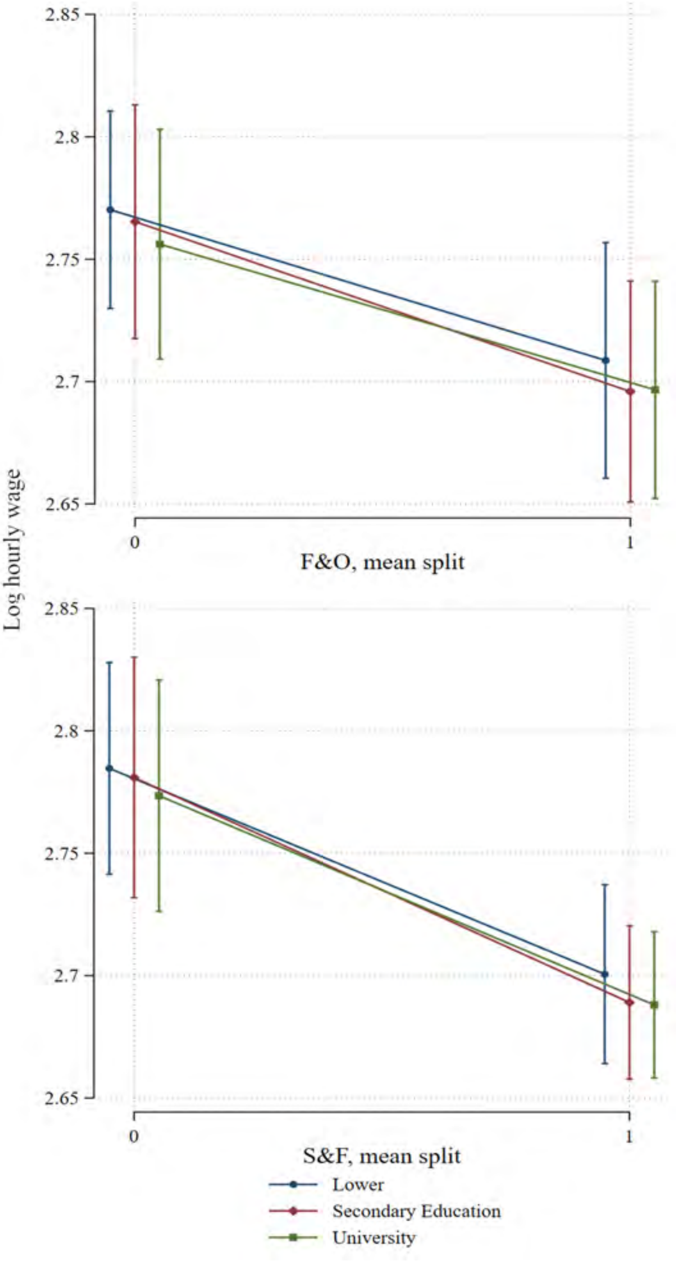


Figure 4.16: Coefficient plots of predicted log hourly wage by levels of automation risk interacted with parental education. Source: Statistics Netherlands, own calculations.

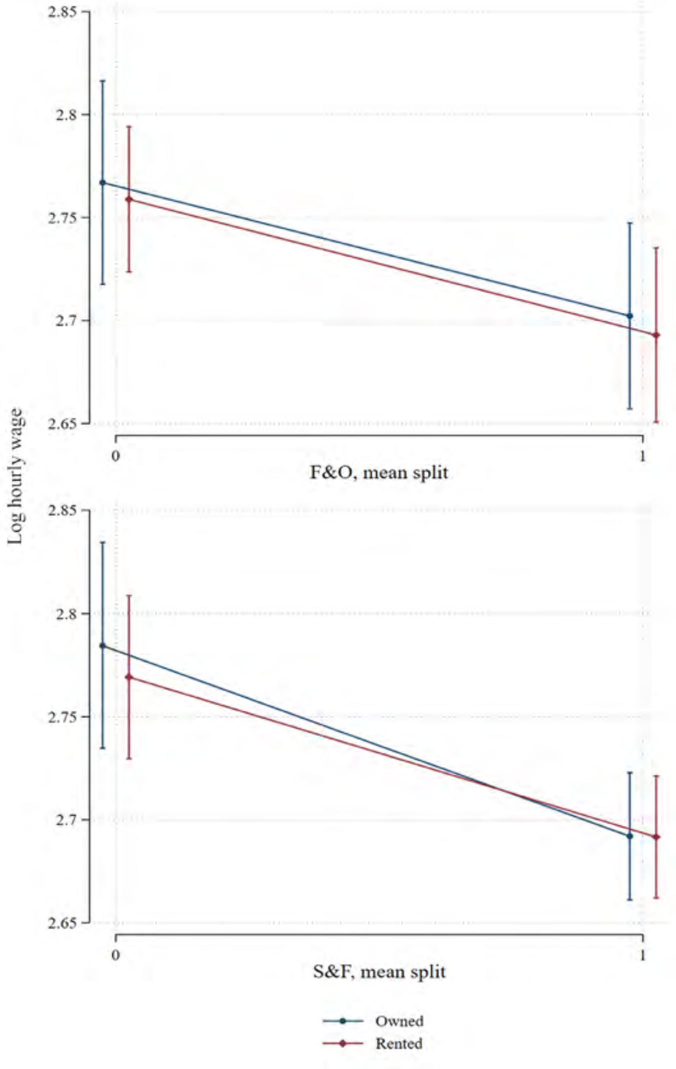


Figure 4.17: Coefficient plots of predicted log hourly wage by levels of automation risk interacted with parental homeownership. Source: Statistics Netherlands, own calculations.

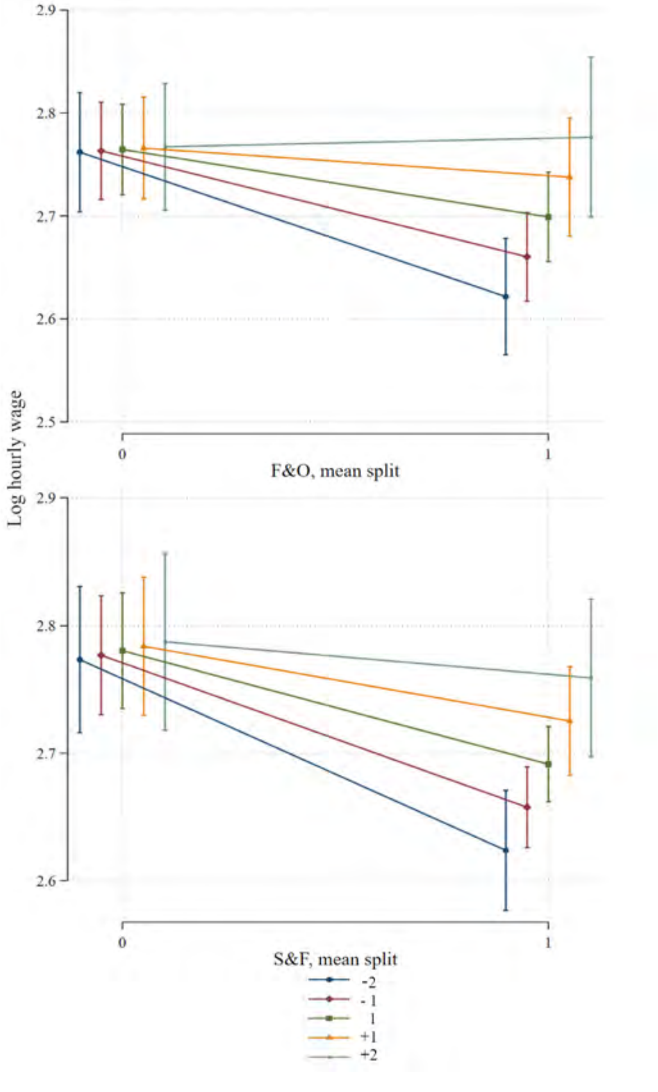


Figure 4.18: Coefficient plots of predicted log hourly wage by automation risk interacted with parental household income (logged, lines represent standard deviations). Source: Statistics Netherlands, own calculations.

4.5 Conclusion and discussion

We have provided the first analysis of the role of automation risk in the early career of VET graduates in the Netherlands. We derived measures of automation risk of VET programs in the Netherlands using the weighted average of automation risk of the occupations that these programs prepare for. We used these data for two research questions. First, we asked how and which VET programs in the Netherlands are exposed to automation risks. We found considerable variation in the exposure of VET programs to automation risk with the lowest automation risks in health and care related fields and the highest risks found in secretarial and administrative VET programs. Second, we asked what this means for school-to-work transitions and early careers of VET graduates in the Netherlands. Using sequence analysis, we found four post-VET trajectories. We hypothesized that automation risks would be associated with an increase in the probability to follow a trajectory characterized by NEET and that it would be associated with an increase in the probability of VET graduates to continue with education. However, we could not find the systematic evidence to support these expectations. This might suggest that the automation risk of VET programs is not (yet) driving young graduates out of employment. In fact, very few VET graduates follow a long-term NEET trajectory at all. We also expected that automation risk would be negatively associated with starting wages and wage growth. Here, we found lower starting wages — but not lower wage growth — for graduates from easier-to-automate VET programs. This might be because we only look at the first ten years of the career and differences in wage growth trajectories would only become apparent at later age. Moreover, in the Netherlands, wage growth is largely determined by collective agreements and wage scales on the sectoral level.

Our analysis is not without limitations. First, we need to address the indirectness of our measures of automation risk. The merging of different occupation codes to Dutch education programs is imperfect, and measurement error is inevitable. We tried to account for this by using different measures of automation risk and by controlling for the occupational linkage, which by design is an indicator for matching quality. However, the number of VET level-fields we could distinguish was low and future studies should aim to differentiate between VET programs more precisely. Future studies should also aim to measure the automation risks of educational programs more directly. Second, we could not confirm that VET graduates work in the occupations they trained for, as there are no data on occupations available in the Dutch register data. Hence, we could not control for the occupation that graduates sort into, nor the task content of their occupation. Third, we only focused on MBO3 and 4. While we based this choice on the notion that these medium-educated graduates will be the most affected by automation risks, future studies could include a wider range of educational degrees. Although the tracked education system will lead to strong path-dependence which would likely necessitate separate analyses for student from vocational and general tracks regardless. Fourth, our results should not be interpreted as causal effects. While we did control for the most important observable confounders and did include individual random effects in the growth curve model, there are time-varying confounders that we could not control for. Still, our results did provide the first descriptive, longitudinal evidence to the debate of automation risk and vocational training.

Young people are often thought to be the most vulnerable in economically uncertain times. Surely, automation will be a challenge to workers in the future and new social inequalities might emerge. Policymakers should remain vigilant of the disruptive nature of labor automation and scrutinize and future-proof the skills that are taught in vocational education.

Chapter 5

How Young Mothers rely on Kin Networks and Formal Childcare to avoid becoming NEET in the Netherlands[1]

5.1 Introduction

In recent decades, women's labor market participation in Western European countries has dramatically increased. Still, many women leave the labor force after having a child (Aisenbrey et al., 2010; Joshi et al., 1996). Even a temporary retreat from work or education may negatively affect the acquisition of human capital and consequently of occupational status and earnings. This can lead to substantial gender wage gaps that emerge around childbirth[2] (e.g., Kleven et al., 2019). One group that is not often studied in this context are young mothers and their school-to-work transition. As they most likely have not yet established a stable career or are still in education, prolonged economic inactivity and educational drop-out could mean a significant source of negative outcomes later in life for themselves and potentially their children. Young mothers face the additional structural conflict of interest between motherhood and education (Sniekers & van den

[1]This chapter is published as Dicks, Alexander, Mark Levels, Rolf van der Velden, and Melinda C Mills. 2022. "How Young Mothers Rely on Kin Networks and Formal Childcare to Avoid Becoming NEET in the Netherlands." *Frontiers in Sociology*, 6(787532), https://doi.org/10.3389/fsoc.2021.787532

[2]Although the gender wage gap cannot be completely explained by the motherhood penalty (Combet & Oesch, 2019).

Brink, 2019). They are more likely ‘**N**ot in **E**ducation, **E**mployment, or **T**raining’ (NEET) (Klug et al., 2019; Netherlands, 2018), have achieved less education, less income, and lower employment probability at a later age (Johansen et al., 2020) as well as a higher welfare dependence (Gibb et al., 2015). Being NEET is correlated with a myriad of negative outcomes, such as negative feelings, lower lifetime income, and a higher risk of social exclusion and disengagement (e.g., Bynner & Parsons, 2002; Eurofound, 2012; Levels et al., 2022; Maguire, 2018). Therefore, it is important to understand which resources can enable young mothers to complete their education and to (re-)enter the labor force. One such resource is social support through kin networks, especially grandparental childcare, which is of great importance to mothers (e.g., Arpino et al., 2014; Hank & Buber, 2009) and to young mothers in particular (Maguire, 2018; Sniekers & van den Brink, 2019; Ypeij, 2009). Hence, in this study, we will study the relationship between the availability of social support networks and childcare for young mothers’ school-to-work transitions.

In this chapter, we will study the role of childcare by kin networks and institutions in The Netherlands. The Dutch setting provides an interesting case study. In the past, the male breadwinner model was the most dominant gender role pattern (Clerkx & van IJzendoorn, 1992). This has only partly changed, and childcare is still considered women’s responsibility (Mills et al., 2014; Sniekers & van den Brink, 2019). This is also reflected in Dutch policies and institutions. Rather than providing extensive leave schemes like other European countries, childcare policies in the Netherlands are reflective of the one-and-a-half-earner model with strong employment protection for part-time workers (Lewis et al., 2008). The one-and-a-half earner model is also reflected in formal childcare arrangements. Dutch parents are reluctant to put their children in full-time formal childcare (Portegijs et al., 2006). In addition to concerns about lacking availability, especially in rural areas (Noailly & Visser, 2009), this reluctance might be explained by long held beliefs about its poor quality care (Leitner, 2003). The cost of childcare is another factor. Generally, the cheaper it is, the higher is the labor force participation of women (Connelly, 1992; Zamarro, 2020). Although economic theory assumes that different sources of childcare are perfectly substitutable, this might not be the case if there are concerns about the quality and availability of public childcare provisions (Arpino et al., 2014; Portegijs et al., 2006; van Ham & Büchel, 2004). And although substantial subsidies are available, childcare in the Netherlands is not subsidized if either parent is not working and not in education (and thus NEET). Young mothers are especially affected by this and often struggle to combine motherhood and education or employment (Sniekers & van den Brink, 2019). There is also a considerable social class gap in childcare use. Among poor households, childcare use is less than half than that of rich households (Mills et al., 2014). The combination of short parental leave and low public support for mothers with children under the age of three leaves the Netherlands with one of the widest coverage gaps of early childcare in Europe, which to close needs family support (Bordone et al., 2017; Saraceno & Keck, 2010).

Based on this, one might ask how young mothers can overcome this lack of institutional support (Uunk et al., 2005). In the Dutch policy regime of 'familialism by default' (Saraceno & Keck, 2010), especially from maternal grandparents will provide childcare. Indeed, the use of informal care in the Netherlands is very high (Mills et al., 2014) and about half of Dutch parents report having received childcare support from the grandparents (Knijn & Liefbroer, 2006). However, for young mothers whose own parents might not yet be in retirement themselves, access to grandparental childcare might be restricted and depend on other factors and strategies as well. For instance, grandparents and young mothers might coordinate their work schedules to fit their needs (Sniekers & van den Brink, 2019). The relationship of childcare by grandparents and other family members and the labor market activity of mothers has been studied in various ways. Most studies find positive associations between grandparental childcare and labor market participation. But depending on the data and methods used, results may vary. We discuss the results, merits, and downsides of previous studies after the introduction. Table C.3.1 gives an overview of these studies.

We merge the literature on mother's labor force participation with the literature on NEET, where we are among the first to use longitudinal data to study NEET (cf. Contini et al., 2019). We aim to understand how the availability of kin support networks and formal childcare contribute to the decision to (a) withdraw from the labor force and education and (b) to reintegrate into the labor force or education. Thereby, we aim to answer the following research questions: *To what extent can the characteristics of young women, their parents, partners, and the institutional context explain why some young mothers a) become NEET or b) exit NEET status?*

To answer these questions, we analyze population-wide longitudinal register data from the Dutch Social Statistical Database (Bakker et al., 2014). These register data are prospective, so that we can observe the whole school-to-work transition and economic activities of all persons involved and without recall bias. Because the data are collected by institutions and not reported by individuals, there are also no issues with reporting bias or panel attrition. Second, the data enable us to observe the whole population of the Netherlands. Since young mothers are a small group, having population-wide data is important. Studies based on most survey data cannot specifically focus on young mothers and often exclude them or other small groups because of sample size issues. In addition to our cohort of interest, we can link their data to data of their extended family and their partners. Most importantly, we can supplement this with detailed geographical data that many studies do not have access to (Compton, 2015). We use discrete-time event history analysis to test the hypotheses derived in the theory section.

5.1.1 Literature review

Before we discuss our approach to this topic, a literature review will help to place this chapter in the wider literature. Using a sample of immigrants in France, Dimova & Wolff (2008) showed that spatial distance to grandparents reduced the provision of grandparental childcare and that the provision of grandparental childcare is positively related to the mother's labor market participation. In a later study, Dimova & Wolff (2011) used the data of ten European countries from SHARE and found strong positive relationships of grandparental care and mother's labor force participation and involvement. They also consider monetary transfer as a possible mechanism, for which they find no evidence. However, by pooling the data of different countries, the interpretation of the average effect might be unclear and hide between-country differences (Aassve et al., 2012). Also, because SHARE relies on the grandmothers as informants, it lacks some information of the mothers, including their income, and information on daughters-in-law. Using the same data and using retirement eligibility as an instrumental variable, Zamarro (2020) found a significant relationship only in the Netherlands and Greece but not in the other countries included in the data. An instrumental variable approach can be useful to approach a causal interpretation. It works, by estimating the effect from an exogenous variable (here retirement eligibility) on the outcome via the variable of interest (childcare by grandparents) while assuming that the only way the exogenous variable changes the outcome is via the variable of interest. That also implies, that the instrument restricts the sample to grandmothers of working age. Naturally, this approach hinges on having exogenous variation in the first place. Aparicio Fenoll (2020) used shifts in the legal retirement age to instrument for retirement status of grandmothers. The author confirmed the positive relationship between grandmothers' increased availability due to retirement with the labor force participation of mothers, but only in countries with low family benefits (which according to the author includes the Netherlands). Using the GGS, Aassve et al. (2012) found a positive relationship between childcare by grandmothers and mothers' labor force participation in Bulgaria, France, Germany, and Hungary. However, after including two instrumental variables, the grandmother being alive and number of siblings, the effect became insignificant in Georgia, Russia, and the Netherlands. While grandparental help is explicitly measured in the Generations and Gender Survey (GGS) data, the study is cross-sectional in design and the authors exclude single mothers, mothers with children under the age of one as well as women who were not survey respondents themselves. Using a family fixed-effects model on longitudinal survey data from the US, Posadas & Vidal-Fernandez (2013) found that grandparental childcare increases the labor force participation of mothers, although not after using the grandmothers' death as an instrument. For Italy, Arpino et al. (2014) found that having grandparents care for the children increases the mother's labor force participation. However, they excluded single mothers because of low case numbers in their survey data. The authors used a similar instrumental variable as Aassve et al. (2012) but extended it to all grandparents being alive, including the parents of the partner. Del Boca (2002) used 'having at least one grandparent alive' as a proxy variable for the availability of grandparental childcare and found that this positively correlates with mother's labor force participation. Similarly, Bratti et al. (2018) found that mothers with children in Italy are more likely to work if their own mother is eligible for retirement. Due to the design of the survey, they had to restrict the sample to cohabitating couples. For Canada, Compton (2015) found that married women with children are more likely to work if their own mother—but not their mother-in-law—lives in close proximity. For single mothers, she did not find an effect on the probability to work but only on working hours. For the US, Compton & Pollak (2014) found that living close to their own mother, and in this case also to their mother-in-law, can increase the probability of mothers of young children to work. Also for the US, Krolikowski et al. (2020) showed that after losing a job, young people living in the same neighborhood as their parents benefit from stronger earnings recovery and that this is mainly driven by childcare. In addition to these mostly positive effects, there might also be downsides to relying on grandparents for childcare. Using the German Socio-Economic Panel, García-Morán & Kuehn (2017) found that living closer to their parents and parents-in-law can increase the likelihood to work for mothers between 25 and 50, but that this comes at the cost of lower wages and longer commutes. However, in the data used, it was not possible to distinguish grandparental childcare from childcare by other relatives. Lastly, using data on working women from the European Social Survey, Abendroth et al. (2012) found no significant correlation between the availability of care support from outside the household and mother's working hours.

All in all, the literature agrees on the positive relationship of grandparental care and labor force participation of mothers. However, there are some limitations with these earlier studies. Few of the listed studies have longitudinal data, hence it is not possible to study exits or entries into the labor force (or education). Another limitation with the used surveys is that the information is gathered from one actor only. Hence, they often lack some key variables for the other actors involved, such as income and economic activity. Few of the existing studies also consider the various forms (formal, informal) of child-care provision at the same time (Blau & Currie, 2006). Yet this is necessary because the availability of formal childcare may substitute or crowd-out informal childcare (Arpino et al., 2014; Bordone et al., 2017; Havnes & Mogstad, 2011). The studies that do consider formal and informal childcare at the same time, mostly rely on between-country variation, thereby masking within-country differences of availability of formal childcare.

Another limitation of previous studies is that they mainly explain income and labor force participation but not participation in education. This is understandable, as they mostly did not focus on *young* women. For young people, however, traditional labor market indicators are of limited relevance (Eurofound, 2012). To better capture vulnerable young people on the labor market, the term NEET was coined as a policy definition in the UK in the 1990s (Furlong, 2006). The term is not without criticism and has been criticized to hide within-group differences between those who are 'merely' unemployed and those who become inactive long-term (Bynner & Parsons, 2002; Furlong, 2006; Maguire, 2015; Yates & Payne, 2006). It has also been questioned how applicable it is to young mothers, as their decision to become NEET might be a voluntar withdrawal from the labor market (Tamesberger & Bacher, 2014). However, evidence from qualitative studies showed that many young mothers would like to participate in the labor market or in education – if they could (Maguire, 2018; Sniekers & van den Brink, 2019; Ypeij, 2009).

5.2 Theory

To understand the effect of childbirth on the labor market participation of women, we start from the framework of work-family fit (Voydanoff, 2005). In this framework, women's decisions regarding the labor market are made by considering the perceived fit of demands and resources in different domains of life. On the one hand, these are demands from work, like working hours and overtime, job demands, and insecurity. These must be balanced with family demands, for example caring for young children. Resources from the family, such as employment and income of the partner and kin support with childcare, can then be used to increase the fit of both domains. We will now lay out the different mechanism for both the partner and the kin support. We follow Begall & Grunow (2015) and also consider the institutional environment in this framework. Furthermore, we extend on Begall & Grunow (2015) by also considering kin support.

5.2.1 Partners

Partners in the household are the most likely candidates for helping with child-rearing. Partners in the nuclear family divide time and effort involved with care work between the two of them. The more a young mother can rely on her partner to help with care work, the less likely it is that she must reduce time on the labor market or in education, and the less likely it is that she becomes NEET. For single mothers, the work-family fit perspective would predict that they cannot rely on the resources of a partner and hence would be less able to achieve a good work-family fit and hence more likely to have to reduce time on the labor market. From this we deduce:

> *Hypothesis 1: Young mothers who have a partner (i.e., are cohabitating or married) are less likely to become NEET and more likely to exit NEET.*

If there is a partner present, different perspectives lead to the same expectation regarding the employment and income of the partner. The work-family fit perspective holds that "family support occurs when one spouse serves as the major family provider so that the other spouse may limit work participation to engage more extensively in family activities" (Voydanoff, 2005, p. 9). *Family economics* and *bargaining* theories predict that specializations and bargaining power between partners in the household determine the division of unpaid care work and paid work in the household (Becker, 1981; Bittman et al., 2003; Lundberg & Pollak, 1996). This would dictate that the higher the partner's income from labor is relative to the young mother's, the higher are the household's opportunity costs for the partner to not work and the costlier it is for the household to have the partner give up labor earning for child-rearing. This goes vice-versa for the young mother's earnings compared to the partner's earnings. Hence, we expect:

Hypothesis 2: The higher the young mother's income relative to the partner's, the less likely it is that she becomes NEET and the more likely she is to exit NEET.

5.2.2 Grandparents

Especially for young mothers in the Netherlands, support from the family is very important (Sniekers & van den Brink, 2019; Ypeij, 2009). Kin support can be understood as the access to resources through the ties of a social network, or social capital (Boisjoly et al., 1995; Coleman, 1988; Portes, 1998). Hence, grandparents who can help raise their grandchild would increase work-family fit. Reduced travel times, lower numbers of adult children, and the fact that grandparents now live longer lives than before has increased the supply of care (Geurts et al., 2015). Especially young mothers often rely on their own parents for childcare (Vandell et al., 2003). Grandparental care has at least three advantages (Portegijs et al., 2006). First, it is often free. Second, because grandparents are often retired, they are very flexible in terms of their time. Fitting the needs of the Dutch part-time culture, grandparental care is also often part-time (Bordone et al., 2017). Third, grandparents are seen as preferred caregivers and perceived as more trustworthy and even more qualified than formal care providers. The security of having a trustworthy, familial source of flexible and free childcare if a child falls ill or a parent has to go on a business trip, work overtime, study, or apply for jobs might enhance young mother's chances of returning to employment or education after having a child even if the available childcare is not used (Compton, 2015; Compton & Pollak, 2014). Yet, the extent to which grandparents can be used as a source for childcare is not the same for everyone. The amount of support they can provide also depends on their own characteristics. The less costly it is for them to provide childcare, the more strongly their own daughters can rely on their support. We will now lay out two mechanisms how grandparental availability to provide childcare increases work-family fit: space and economic activity.

Spatial distance

While some forms of support, like financial support, are not affected by spatial distance, childcare is hands-on and requires physical presence. The closer the grandparents live to their daughters (and daughters-in-law), the less traveling time it takes to get to their daughter's house, and the less costly it is for them to provide help with childcare. This can enable young women to participate in education or on the labor market. Indeed, proximity to grandparents has been shown to be an important predictor of different fertility related outcomes, such as childbirth (García-Morán & Kuehn, 2017; Thomese & Liefbroer, 2013), frequency of grandparental childcare (Dimova & Wolff, 2008; Ho, 2015; Knijn & Liefbroer, 2006; Thomese & Liefbroer, 2013; Zamarro, 2020), and of the daughter's labor force participation (Compton & Pollak, 2014; García-Morán & Kuehn, 2017). Older adults were also shown to be more likely to move towards their children if they have grandchildren (van Diepen & Mulder, 2008). Sharing a household with their parents has also been shown to increase labor force participation and grandparental childcare provision (Leibowitz et al., 1992; Ogawa & Ermisch, 1996; Sasaki, 2002; Vandell et al., 2003). From this we deduce:

> *Hypothesis 3: The more grandparents live in close distance to the young mother, the less likely it is that she becomes NEET and the more likely she is to exit NEET.*

Economic activity

Within the extended family, cost-benefit calculations like the ones within the nuclear family are made. For instance, as wage growth and human capital investments flatten out with age (Becker, 1981; Ben-Porath, 1967), having grandparents to provide childcare for them would incur lower family-wide opportunity costs than if the mothers themselves stopped working. It might thus be rational for grandparents to reduce working hours and give up labor earnings so that their daughter can invest in her life-time earnings while she is still in the phase of steep wage growth (see Krolikowski et al., 2020). Hence, the availability of grandparents to supply childcare depends on their own employment and living situation (Bratti et al., 2018; Hank & Buber, 2009). Following this logic, we may assume that grandparents who work part-time or who depend less on income from their own labor have lower opportunity costs for the time not spent on the labor market and are therefore more likely to provide childcare. As a result, young mothers could more strongly rely on their support with childcare (Gray, 2005; Hank & Buber, 2009). However, grandparents who themselves need care are less available for childcare. Hence:

> *Hypothesis 4a: Young mothers whose parents work part-time, who are retired, or receive social benefits, are less likely to become NEET and more likely to exit NEET than young mothers whose parents are working full-time.*

An alternative mechanism is possible as well. Parish et al. (1991) found that employment of nearby kin increases the employment of mothers themselves. They suggested that this is in line with a "culture-of-employment"-hypothesis, from which follows:

> *Hypothesis 4b: Young mothers whose parents are working, are less likely to become NEET and more likely to exit NEET than young mothers whose parents are not working.*

5.2.3 Formal childcare

Next to their social support networks, young mothers could also rely on institutions like formal childcare. We consider the availability of formal childcare as a type of institutional resource to increase work-family fit. Childcare facilities must be nearby, have capacity available, be affordable, and be in line with the quality demands of the parents. Spatial distance has been described as the most important factor for choosing a childcare facility (Berkhout et al., 2009) and there are concerns of sufficient availability, especially in rural areas of the Netherlands (Noailly & Visser, 2009). From this follows that:

> *Hypothesis 5: The more formal childcare institutions are nearby, the less likely it is that young mothers become NEET and the more likely it is that they exit NEET.*

5.2.4 Moderation of informal childcare by formal childcare

Different welfare regimes and family policies likely influence the need for kin support (Saraceno & Keck, 2010). Several arguments were made in the literature. First, the argument of crowding-out of private transfers by public transfers holds that a strong welfare state reduces intergenerational solidarity (Cox & Jakubson, 1995; Igel & Szydlik, 2011) and that informal care would only be provided in case of a lack of public childcare provision (Künemund & Vogel, 2006). In opposition to this functional understanding of intergenerational solidarity stands the argument of crowding-in. It holds that more expansive welfare provisions complement and stimulate intergenerational solidarity (Daatland & Lowenstein, 2005; Igel & Szydlik, 2011). To reconcile these two hypotheses, the concept of 'mixed responsibilities' suggests that formal and informal childcare provisions interact (Attias-Donfut & Wolff, 2000; Bordone et al., 2017; Igel & Szydlik, 2011). For example, while the welfare state provides basic, regular care, the family might concentrate on less time-consuming, informal care (Igel & Szydlik, 2011). Indeed, public spending on childcare increases occurrence of childcare by grandparents but decreases its frequency (Igel & Szydlik, 2011). In the Netherlands, childcare by grandparents is used to complement part-time work arrangements and the lack of formal childcare and leave schemes (Bordone et al., 2017; Geurts et al., 2015; Igel & Szydlik, 2011; Portegijs et al., 2006). These hypotheses mostly consider the size of the welfare state, family policies, and childcare expenditure on a national level, although they can be adapted to the local level as well. In our case, availability of childcare facilities nearby should interact with grandparental childcare. We cannot distinguish between the different mechanisms as we do not observe frequency or occurrence of grandparental childcare. However, we can distinguish crowding-out from crowding-in. Hence, we expect that:

> *Hypothesis 6: The higher the availability of formal childcare nearby, the smaller (crowding-out) or larger (crowding-in) is the relationship between grandparental availability and the probability of young mothers to become and exit NEET.*

5.3 Data and methodology

5.3.1 Data and population

We use population-wide register data from the Dutch Social Statistical Database (SSD) (Bakker et al., 2014). For the entire population, we know of the educational enrolment, the monthly economic activities, income, and working hours and merge these into a long data file. Using the encrypted personal identifier, we can link young mothers to their parents, their children, the fathers of their children, and their partners. We then add basic demographic data to each of the personal identifiers. Every person is then linked to an encrypted address identifier which we use to calculate distances between them.

We define our target population in the following way. We start with data on each child born in the Netherlands between 2012 and 2014 to which we merge the personal identifier of their legal mother[3]. We restrict the sample to women born in the Netherlands who were between 16 and 24 when they had their first child. This yields a population of N = 32,365 young mothers with

[3]It is possible that the legal mother is not female. We only include cases of female legal mothers.

a median birth year of 1990. We expand the data so that every row is equal to one monthly observation per individual. This person-period file consists of N = 2,726,604 person-month observations beginning 24 months before first childbirth to 60 months after. After list wise deletion of observations with missing values on key variables, our final sample includes N = 31,938 young mothers. Tables 5.1, 5.2, and 5.4 show descriptive statistics of the variables used in the analysis by actor and domain. The following section describes the operationalization of these variables.

5.3.2 Monthly activity

Monthly activity is the central data in this study and both basis for dependent and independent variables. It is obtained by merging three datasets from the Dutch register data (SSD) (Bakker et al., 2014). First, we use monthly data on the main economic activity which is defined as the main source of income. Originally, this variable has twelve states: (1) employee, (2) director/major shareholder, (3) self-employed, (4) other self-employed, (5) recipient of unemployment insurance, (6) recipient of welfare, (7) recipient of other social benefits, (8) recipient of illness and disability benefits, (9) recipient of pension, (10) (not yet) pupil/student with income, (11) (not yet) pupil/student without income, (12) other without income. Similar to the other chapters, we collapse states 1-4 into 'Working', states 5-9 and 12 into 'NEET', and states 10-11 into 'Education'. Second, we use a dataset that includes calendar data on registrations in publicly funded education to better differentiate among different types of education. We merge the two datasets, where education overwrites other states. We do this because in some cases the two data sets contain different information, for example when students or apprentices earn an income. We argue that in such cases, the defining state is being in education and not earning an income. Primary education, practical education, and secondary education are grouped as "Secondary Education and below". We distinguish two main types of further education, Vocational Training and Higher Education. Third, we make use of data on employment contracts with which we can further split-up the state of 'Working' into full-time and part-time. We define part-time working as less than three full working days per week (24 hours). In most cases, parental leave should be included as employment - if contract or income do not change during it. We repeat these data handling steps for the parents of the mother, the current partner (in case one is present), and the parents of the partner. We obtain the monthly activity for all those key actors in the same way. Although we do code the monthly activity for the parents differently than for the young mother and her partner. For the parent generation, we distinguish between Working (and Education as those are only very few), Unemployment/Welfare benefits, Sickness/other benefits, Pension, and other.

5.3.3 Young mother's variables

Enter/Exit NEET: Our main dependent variables are dummy variables scored 1 in the month a woman experiences an event and 0 in all previous months. Based on the monthly activity, we define the following events. The variable 'Enter NEET' takes on the value of 1 in the months a young mother becomes NEET for at least three months and 0 in case of no change. The variable 'Exit NEET' takes on the value of 1 if a young mother who is NEET starts work or education for at least three months and 0 in case of no change. In total, we record 35,677 entries into NEET and 33,400 exits out of NEET. In the appendix in Figure C.4.1, we show that the choice of the event defined as entering a state for one month instead of our preferred definition as an entry into a new state for at least three months does not change our conclusions.

Prior economic activity of young mothers: Based on the monthly activity data, we create a time-constant variable of the modal activity of the young mother between 24 and 12 months before her first birth. We distinguish NEET, part-time work, full-time work, secondary education, vocational education and training, higher education.

Household situation: We link the personal identifiers to the household data set from which we retrieve the variable household type, which we recode into single (1), cohabitating (2), and married (3).

Immigration background: We differentiate between persons without immigration background (two parents born in the Netherlands) and a second-generation immigration background (two parents born in the Netherlands). In addition, we distinguish between seven parental origin categories, Dutch, Caribbean, Moroccan, Surinamese, Turkish, Western and Non-Western. Given our research question being primarily focused on kin support, we exclude first generation immigrants because often there are no parents that we can identify.

Urbanization and province: We account for urbanization because the real travel time might differ between rural and urban areas. Urban areas also have a higher density of formal childcare. At the same time, the labor market and education structures are different in urban areas. For this, we distinguish (0) rural from (1) urbanized and (2) highly urbanized municipalities. In addition, the provinces in the Netherlands differ in size, density, population, economic sectors, geography, and local culture. All these are potential confounders that affect both available support and probability to be NEET. Hence, we control for the provinces in all models.

Time: In all models, we include *time relative to the first birth* as the piecewise constant baseline hazard. After consideration of the observed monthly hazards shown in Figure 5.1, we decide on grouping the following months into piecewise constant dummy variables: 24 to 13 months before first birth, 12 to 6 months before first birth, 5 to the month of first birth, 1 to 6 months after first birth, 7 to 24 months after first birth, 15 to 60 months after first birth. Additionally, we include *age (centered at sample mean)*, *age-squared*, and the *current activities' spell length in months*.

Table 5.1: Summary statistics of key variables of young mothers. Source: Statistics Netherlands, own calculations.

Young mothers' characteristics	Freq.	%/Mean (SD)
Household situation		
Single	16,186	50.7
Cohabitating	10,012	31.3
Married	5,740	18.0
Immigration background		
Dutch	25,210	78.9
Caribbean	508	1.6
Moroccan	1,301	4.1
Surinam	1,381	4.3
Turkish	1,250	3.9
Western	1,474	4.6
Non-Western	814	2.5
Mothers' activity before birth		
Higher Education	2,435	7.6
NEET	3,686	11.5
Secondary Education and below	1,477	4.6
Vocational Training	8,712	27.3
Working	10,574	33.1
Part-time Work	5,054	15.8
Urbanization		
Rural	13,716	42.9
Urbanized	10,518	32.9
Highly urbanized	7,704	24.1
Province		
Drenthe	1,015	3.2

Young mothers' characteristics	Freq.	%/Mean (SD)
Flevoland	1,158	3.6
Friesland	1,481	4.6
Gelderland	3,972	12.4
Groningen	1,383	4.3
Limburg	1,796	5.6
Noord-Brabant	3,628	11.4
Noord-Holland	4,339	13.6
Overijssel	2,363	7.4
Utrecht	2,046	6.4
Zeeland	992	3.1
Zuid-Holland	7,765	24.3
Age in years	31,938	21.09 (1.85)
N (Young mothers)	31,938	100

5.3.4 Partner's variables

Partner's activity before birth

Based on the monthly activity data, we create a time-constant variable of the modal activity of the partner between 24 and 12 months before the first birth of the young mother. This variable is coded zero in case there is no partner present. By adding the household situation variable to the model, the coefficient of partner's activity is to be interpreted among women who are cohabitating or married.

Relative wage

We compare the wage of the young mother to the wage of the partner. Here, we distinguish between several levels of relative wage between less than 33% up to 100% and more. In addition, we distinguish cases in which the young mother, the partner, or both do not earn any wage. In case there is no partner, the variable is coded as 'no income from partner'. Hence, the coefficient of relative wage is an additive one and only interpreted if the household situation is cohabitating or married.

Table 5.2: Summary statistics of key variables of partners of young mothers. Source: Statistics Netherlands, own calculations.

Partner characteristics	Freq.	%
Immigration background		
Dutch	12,533	79.6
Caribbean	166	1.1
Moroccan	787	5.0
Surinam	340	2.2
Turkish	829	5.3
Western	754	4.8
Non-Western	343	2.2
Partners activity before birth		
Education	4,016	25.5
Working	10,258	65.1
NEET	953	6.1
Part-time Work	525	3.3
Wage as percentage of partner's wage		
no income from either	2,771	17.6
no income from YM	3,147	20.0
up to 33%	619	3.9
33% to 66%	2,646	16.8
66% to 100%	2,530	16.1
100% and more	1,013	6.4
no income from Partner	3,026	19.2
N (Partners)	15,752	100

5.3.5 Grandparent variables

Economic activity of grandparents

We obtain the monthly activity the same way for all other actors and as described in the paragraph on monthly activity. That is, we obtain a categorical variable distinguishing Education, Full-time working, Part-time working (<24 hours per Week, via (S)POLISBUS), NEET, and absence (when no actor can be matched). For grandparents, instead of NEET, we distinguish between receiving between welfare/unemployment, pension, and disability benefits.

Distance to grandparents and availability in immediate vicinity

Based on the household address data, we create address pairs of young mothers and their parents as well as their partner's parents. We then calculate the distance (measured as the crow flies) for all address pairs using the "Distance tool" provided in the remote access environment of Statistics Netherlands. Distance measured as the crow flies correlates strongly with actual travel distance (.966) and time (.947) (Rietveld et al., 1999). We then count the number of grandparents living within 3 km of the young mother. In the Dutch context, this corresponds to the surface area of a medium-sized town. Table 5.3 shows the distribution of the number of grandparents.

5.3.6 Number of childcare facilities

We use the number of childcare facilities within 3 km travel distance which we interpret as a measure of ease of access and availability of formal childcare. We merge this information to each person-period observation via the encrypted address identifier. This measure is only available from 2012 onwards. We use the values from 2012 for 2010 and 2011 and assume that in those years, distances between addresses and childcare facilities have not changed substantially. Table 5.3 shows the distribution of the available childcare facilities as well as the distance to grandparents.

Table 5.3: Summary statistics of formal and informal childcare availability variables. Source: Statistics Netherlands, own calculations.

Childcare availability	Freq.	%
Number of grandparents within 3 km radius		
0	7,186	22.5
1	5,627	17.6
2	12,249	38.4
3	2,823	8.8
4	4,053	12.7
Childcare facilities within 3 km radius		
0	1,290	4.5
1-3	6,415	22.3
3+	21,044	73.2

Table 5.4: Summary statistics of key variables of grandparents of young mothers' first child. Source: Statistics Netherlands, own calculations.

Grandparents' characteristics	Freq.	%
Maternal grandmother matched		
No	891	2.8
Yes	31,047	97.2
If yes: Economic activity		
Part-time	8,976	28.9
Full-time	9,761	31.4
Unemployment/Welfare benefits	3,747	12.1
Sickness/Other benefits	2,783	9.0
Pension	491	1.6
other	5,289	17.0
Maternal grandfather matched		
No	3,346	10.5
Yes	28,592	89.5
If yes: Economic activity		
Full-time	21,478	75.1
Unemployment/Welfare benefits	2,313	8.1
Sickness/Other benefits	2,929	10.2
Pension	979	3.4
other	893	3.1
Paternal grandmother matched		
No	5,934	18.6
Yes	26,004	81.4
If yes: Economic activity		
Part-time	6,791	26.1
Full-time	7,433	28.6
Unemployment/Welfare benefits	2,738	10.5
Sickness/Other benefits	2,355	9.1
Pension	1,457	5.6
other	5,230	20.1

Grandparents' characteristics	Freq.	%
Paternal grandfather matched		
No	7,971	25.0
Yes	23,967	75.0
If yes: Economic activity		
Full-time	16,276	67.9
Unemployment/Welfare benefits	1,813	7.6
Sickness/Other benefits	2,782	11.6
Pension	2,541	10.6
other	555	2.3

5.4 Analytical strategy

To test our hypotheses, we estimate discrete-time event-history models with repeated events and individual random effects. First, we model the risk for young women to become NEET for at least three months during 24 months before until 60 months after the time of first childbirth, given that they were working or in education before. Second, we model the risk of young women who are NEET for at least three months to exit the NEET status for at least three months.

5.5 Results

The likelihood to enter and exit NEET over time is shown in Figure 5.1. The likelihood of entering NEET is low before pregnancy, increases during pregnancy, and decreases again after birth to a similar level as before pregnancy. Hence, if young mothers did not become NEET shortly before birth, the likelihood to become NEET in the five years after is rather low. We see a similar, mirrored pattern, for the likelihood of exiting NEET. It decreases during pregnancy, and then sharply increases just after birth. After birth, the likelihood to exit NEET decreases again and stays on a lower level than before the pregnancy. Hence, if young mothers do not exit NEET right after birth, the likelihood to exit is lower than before pregnancy. Because these relationships are not easily captured by a functional form, we include time relative to birth as a stepwise function, shown as dashed lines in Figure 5.1.

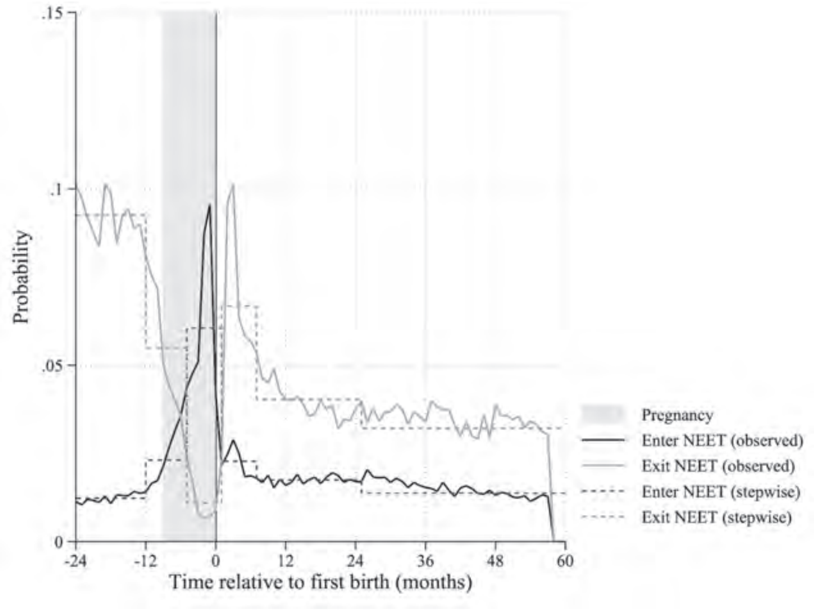


Figure 5.1: Probabilities and step functions of entering and exiting NEET around the time of first childbirth. Source: Statistics Netherlands, own calculations

We first discuss hypothesis H1 on partner availability. Results are shown in Figure 5.2 and based on the full model shown in Table C.1.1. As expected, young mothers who are currently cohabitating (b = -.049) or married (b = -.078) are less likely to become NEET and more likely to exit NEET status (b = .154 and b = .111, respectively). We therefore accept Hypothesis H1. In addition, if the partner was working full-time, young mothers are less likely to become NEET (b = -.294) and more likely to exit NEET (b = .217). We do not find significant differences for partners who worked part-time, nor for becoming NEET. However, young mothers, whose partner was NEET are less likely to exit NEET (b = -.161).

Next, in hypothesis H2 we expected that the higher the relative income of the young mother compared to her partner the lower the likelihood for her to become NEET. We find evidence to suggest that this is the case. The coefficients of the relative wage variable are coded zero in case there is no partner present. Within this group, the higher the share of the young mother's wage income compared to the partner, the less likely she is to

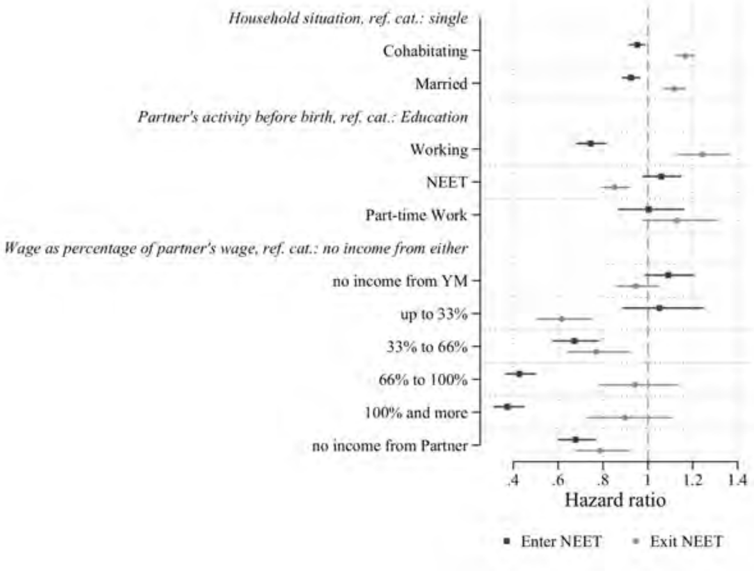


Figure 5.2: Coefficients of partner characteristics from discrete-time event-history analysis (hazard ratios) of entering and exiting NEET. Full model shown in the appendix. Source: Statistics Netherlands, own calculations

become NEET. Comparing the coefficients, this effect tends to increase with the size of the relative share and is highest in case of income parity or when the young mother earned more than her partner. However, also if the partner did not earn before birth, the likelihood to become NEET is decreased as well. For exiting NEET, the pattern is less clear. We find that having a low relative share of the wage within the relationship is correlated with a decreased likelihood to exit NEET. Note that this is only relevant for young mothers who worked and who have a partner who worked. Within this group, a low share of the income rather than parity, is correlated with a lower likelihood to exit NEET. Overall, we find the results to be in line with the argument made in H2 and therefore accept H2. However, we also find that having no income from the partner is negatively correlated with both, the likelihood to enter NEET and exit NEET. This is a special case of the '100% and more' category, with the addition that the income from the partner is not only much smaller but non-existent. Hence, the finding to 'Enter NEET' is in line with the finding that having a higher share of the income is correlated with a lower NEET risk. We tentatively interpret this as evidence for a need to work, that arises from a lack of material support from the partner. In the case of exiting NEET, the context is different because the current activity is different. All the young mothers in this estimation sample are currently NEET. In this case, having a partner who was not earning income while having earned income herself, decreases the risk to exit NEET. Meaning, that once these young mothers do become NEET (against the odds, as the negative coefficient in the 'Enter NEET' model shows), they have a lower likelihood to exit NEET. We tentatively interpret this as a lack of support for exiting NEET.

Figure 5.3 shows the results to test hypothesis H3 on the number of available grandparents in the immediate vicinity. We expected that the more grandparents live within 3 km of the young mother, the more potential support young mothers can access and thereby decrease the likelihood to become NEET and increase their likelihood to exit NEET status. In both cases we find the expected pattern. First, if either one of the grandparents is matched in the data, which we interpret as being an available source of support, decreases the likelihood of becoming NEET and increases the likelihood of exiting NEET. The only exception is the maternal grandmother; however, this is likely due to the lack of variation in this variable (see 5.4, 97.2% of young mothers have their mother matched in the data). In addition, compared to not having any grandparents nearby, young mothers with two (b = -.105), three (b = -.169), or four (b = -.275) grandparents nearby are less likely to become NEET. We do not find a significantly lower likelihood for one grandparent nearby (b = -.024). However, these coefficients need to be interpreted in addition to having at least one grandparent matched in the data, and a single grandparent living nearby is likely a case of divorce or death, which is likely to change the family structure itself. For exiting NEET, the pattern is very similar, although here we do find the expected coefficient also for the first grandparent. Compared to not having any grandparents nearby, young mothers with one (b = .072), two (b = -.152), or three (b = -.144), or four (b = .213) grandparents nearby are more likely to exit NEET status. Following this, we accept Hypothesis H3.

Next, we turn to hypothesis 4a and 4b on the economic activity mechanism of grandparental availability. We do not find significant differences in the likelihood to enter and exit NEET for part-time working grandmothers compared to full-time working grandmothers. In addition, we find that having an unemployed (b=.191) or sickness benefits receiving mother (b = .159) is correlated with a higher likelihood to become NEET for young mothers. While the result for receiving sickness benefits is in line with the availability hypothesis H4a, the results for receiving welfare benefits are

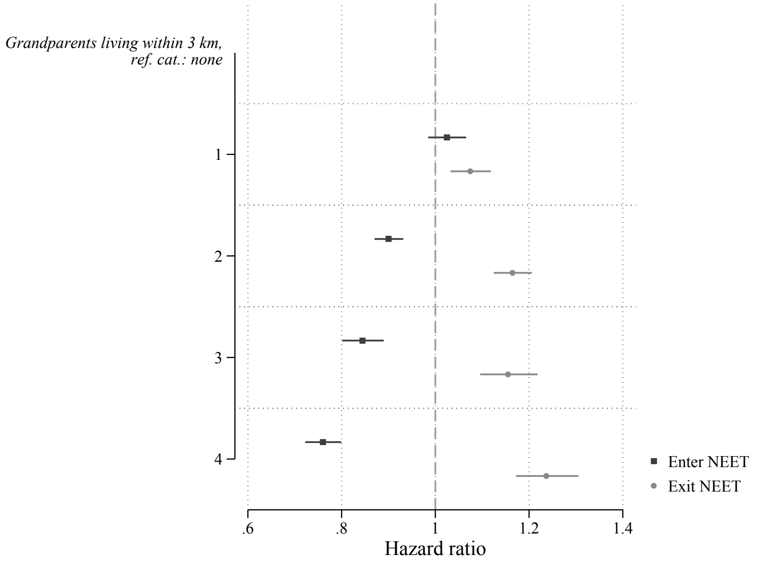


Figure 5.3: Coefficients of grandparental availability within 3 km from discrete-time event-history analysis (hazard ratios) of entering and exiting NEET. Full model shown in the appendix. Source: Statistics Netherlands, own calculations

more in line with social class and culture-of-employment arguments which we formulated in hypothesis H4b. For the other family members, the results are largely in line with those of the maternal grandmother.

Lastly, we expected that the availability of formal childcare would be correlated with a lower likelihood to enter NEET and a higher likelihood to exit NEET. However, we do not find the expected results, shown in Table 5.5. We further expected that the availability of formal childcare moderates the role of informal childcare. Results are shown in Table C.2.1. In line with our expectation, we find that if there are no grandparents nearby, the availability of formal childcare is correlated with a lower likelihood for young mothers to become NEET (b = -.161 and b = -.218), although not with a higher likelihood to exit NEET. Vice versa, if there is no formal childcare nearby, having more grandparents nearby translates to a lower likelihood to become NEET and a higher likelihood to exit NEET. We furthermore find some evidence for the crowding-out mechanism of informal childcare. To help

Table 5.5: Discrete-time event history analysis of formal childcare availability, logistic regression of entry into and exit out of NEET.

	Enter NEET		Exit NEET	
	b	SE	b	SE
Number of childcare facilities within 3km, ref. cat.: No				
1-3	-0.065	0.037	0.017	0.039
3+	-0.039	0.037	-0.003	0.039
Constant	-4.085^{**}	0.075	-1.783^{**}	0.076
Individual-level random effect	0.495^{**}	0.016	0.331^{**}	0.017
Events	33,180		31,292	
Persons	30,658		23,858	
Person-months	1,772,469		786,175	
ICC	0.131		0.091	
-2LL	-150916.657		-114909.461	

* $p < 0.05$, ** $p < 0.01$
Based on full model, variables not shown: Time to birth (piecewise constant), Number of children, Mother's prior economic activity, Immigration background, Age, Age-squared, Length of current spell, Urbanization grade, Province, Partners prior activity, Partner's immigration background, Relative wage, Grandparental activity.

interpretation of the interaction, we show them in Figure 5.4. The horizontal axis shows the number of grandparents within 3 km. The lines represent the predicted probabilities for young mothers to become NEET who live in an area without formal childcare facilities nearby (solid blue), 1-3 childcare facilities nearby (red dashed), and more than 3 facilities nearby (green dash-dotted). As more grandparents are available, all three lines decrease towards the right side of the plot. However, the line for no childcare facilities nearby decreases steeper than the line for 3 or more facilities nearby, meaning that the role of the availability of grandparents becomes less important as the number of formal childcare facilities increases. It should also be noted, that the marginal effect of one additional grandparent is qualitatively different from having an additional pair of grandparents. It is also much less likely that one has exactly one or three grandparents rather than having none, two, or four living within 3 km as that implies divorce or widowhood. The lower precision of the estimates can also be seen in Table C.2.1 where the coefficients of 1 and 3 grandparents are not significant.

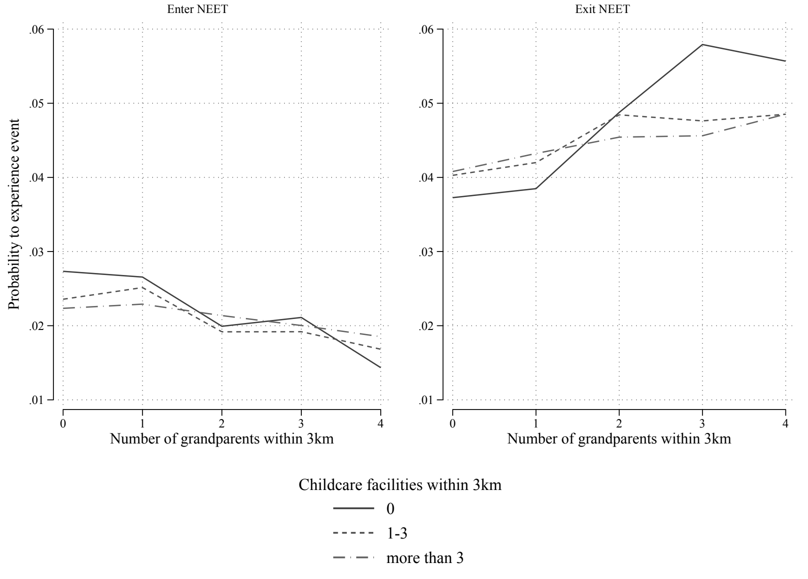


Figure 5.4: Predicted probabilities of entering and exiting NEET for different levels of available formal and informal childcare support. Full model shown in the appendix. Source: Statistics Netherlands, own calculations

5.6 Conclusions and discussion

We investigated the role of availability of informal and formal childcare for the economic and educational situation of young mothers in the Netherlands. First and foremost, we found that social support from partners and from grandparents is important to young mothers in the Netherlands and that we can confirm prior evidence from qualitative studies (Sniekers & van den Brink, 2019; Ypeij, 2009). We showed that there are significant associations of availability of informal childcare and the likelihood to become and exit NEET for young mothers. Young mothers with a partner and with more bargaining power in the household are less likely to become NEET and more likely to exit NEET. Young mothers with more grandparents living nearby can more readily rely on their help with childcare. This is in line with previous research showing the importance of geographical distance for the frequency of grandparental childcare (Dimova & Wolff, 2008; Ho, 2015; Knijn & Liefbroer, 2006; Thomese & Liefbroer, 2013; Zamarro, 2020), and the daughter's labor force participation (Compton & Pollak, 2014; García-Morán & Kuehn, 2017). For grandparents who live nearby, travel time is less of an opportunity cost than for grandparents who live further away. Their childcare can be used more efficiently and more spontaneously, aiding young mothers in navigating the challenges they face in education and on the labor market. We also found that the availability of formal childcare does not have the overall strong relationship with NEET risks that we expected. This is likely because a good *spatial* coverage of childcare facilities exists. However, in case of no grandparents around to help, young mothers do indeed rely on formal childcare and vice versa the role of grandparents is strongest when no childcare facilities are around. This is in line with previous evidence on interaction of informal childcare and formal childcare (Attias-Donfut & Wolff, 2000; Bordone et al., 2017; Igel & Szydlik, 2011; Künemund & Vogel, 2006). Unfortunately, we did not have access to data on the actual usage of formal childcare, nor on the capacity of the facilities. Another aspect of formal childcare that we could not directly address are its costs. We speculated in the introduction, that the fact that childcare subsidies are only paid if both parents are working or in education might be problematic for young mothers. While we do find that being NEET and having a partner who is NEET is negatively correlated with exiting NEET, the lack of access to subsidies in these cases is just one of multiple causal pathways. Without usage data, or an external source of variation in access to subsidies it is difficult to properly disentangle these. Naturally, our approach using register data has its strengths but also some shortcomings. While we do not have to rely on potentially selective survey data, we cannot directly measure the actual provision of childcare. Therefore, our results can only be interpreted as availability and not as provision. Of course, the presence of grandparents does not mean that every young mother also uses this access for childcare. However, this also means that the 'true effect' of grandparental provided childcare is likely larger than the coefficients of presence that we observe. Hence, our analyses are to be interpreted like intention-to-treat effects (Arpino et al., 2014), with the important caveat that we only control on observable characteristics and therefore explicitly refrain from a causal interpretation.

While the application of register data also helped us to minimize the risk to overlook small groups and to eliminate common issues with survey data such as panel attrition, our data did also lack some important variables to further interpret our findings. Future research should therefore try to combine survey and register data.

CHAPTER 6

Conclusion

For young people, the transition from school to work is a crucial phase in their life course. Leaving school, following a vocational training, or studying in higher education, and then finding work are important steps towards economic independence and adulthood. However, for some, this transition is the beginning of economic and educational inactivity. In fact, as described in **Chapter 2**, a long-term NEET trajectory is reality for a sizeable minority of young adults in the Netherlands in the cohort under study. And, as also described in **Chapter 2**, this can lead to considerably lower incomes at age 30. Such disengagement of young people on the labor market is costly, not only for the individual, but also for society. In 2011, the overall costs of young people being NEET in the EU was estimated to be €153 billion, or about 1.2% of the EU's GDP. While the NEET rate, and therefore the total costs of NEET for the Netherlands are below European average, the missing individual contributions in terms of foregone earnings, unpaid taxes, and general loss of social contributions and civic participation in the Netherlands are large (Eurofound, 2012). In addition, for the individual, becoming long-term NEET means not accumulating experience and skills, not accumulating income and wealth, and possibly becoming seriously disengaged from society.

The aim of this thesis was to advance our understanding of such disengagement and of problematic school-to-work transitions in the Netherlands and to study and explore possible reasons why and when young adults become, stay, or stop being NEET. To this end, I have presented four chapters, each zooming in on one specific aspect. I have started in **Chapter 1** to lay out the previous literature and criticism of the NEET concept. Previous research on NEET has often been limited by a lacking theoretical framework and the unclear concept of NEET itself, paired with the limitations of cross-sectional data and a lacking concept of time. I have argued in **Chapter**

1, that the key to understand NEET is a holistic and dynamic perspective. If there is one take-away from this thesis, then it is this: NEET is not a state but a process. NEET is, or at least should be seen as, a dynamic state, and certainly not a diagnosis or group name. Don't call them "the NEETs". Likely due to the use of cross-sectional data, some of the most influential publications on NEET youth refer to the group as a whole as "NEETs" and ask question like "Who are the NEETs in Europe?" (e.g., Eurofound, 2012). Such vocabulary is misleading and possibly stigmatizing. NEET must be embedded in the school-to-work transition, in which a long-term NEET trajectory is to be understood as a failed–or at least delayed–school-to-work transition. This premise has guided the four empirical chapters presented in this thesis. We need to do this to better distinguish between transitory NEET states and long-term trajectories. In the following sections, I will briefly summarize the Chapters 2-5, discuss the findings, and give an outlook on possible future research.

6.1 Summary of main results and contributions

In **Chapter 2**, I have described the Dutch policy context and explored Dutch youth's school-to-work trajectories using sequence and cluster analysis. To recapitulate, the Netherlands have the lowest NEET rate in the EU and a well-functioning transition system with a vocational education system that is marked by high specificity and institutional linkages. However, those youths who do become NEET might be especially negatively selected and could be at a real risk to become stuck in that state. The most important finding of this chapter is that experiencing one month of NEET is widespread but not deterministic of a failed school-to-work transition. Only 6.7% of young people who experience one month NEET also experience a long-term NEET trajectory. Another 10.9% follow a potentially problematic trajectory that leads into NEET later. However, becoming long-term NEET goes along with a substantially lower income at age 30. Furthermore, I showed that women are more likely than men to experience long-term NEET, that youth with an immigrant background are more likely to become long-term NEET than those with two Dutch-born parents, and that youth from lower socioeconomic backgrounds are more likely to become long-term NEET than youth from a higher socioeconomic background. But the strongest predictor of long-term NEET trajectories was early school leaving.

Based on the exploratory results and grounded in the life course principle of *human agency*, I turned my attention to additional explanatory mechanisms for long-term NEET trajectories. Specifically, in **Chapter 3**, I have focused on social class, human capital, occupational aspirations, and personality. Together with my co-authors, I first hypothesized that youth from higher socioeconomic origin, from academic track in secondary education and those with higher cognitive abilities have a lower likelihood to become NEET. We found evidence for the first two but not for the latter. This is likely due to the measurement of cognitive skills. First because it is being mediated by educational tracking, and second, because of the gap between measurement (at age 12) and leaving school (around age 17-18). We hypothesized that youth who have unclear plans for their future and whose plans for their occupational future do not line up with their educational future, would struggle during the school-to-work transition. Non-aligned aspirations might be a sign that youths are misinformed about the education system and the workings of the labor market and that they might be forced to reconsider and compromise later-on (Furlong & Biggart, 1999). However, unlike previous research (Sabates et al., 2011; Staff et al., 2010; Yates et al., 2011) we did not find strong evidence that uncertain or misaligned occupational aspirations increase the likelihood to follow a long-term NEET trajectory. We interpret this lack of strong effects in the context of the highly stratified educational system of the Netherlands. In such a system, students do not need to have clear plans because for the most part, they are following the educational trajectory they were assigned to after primary school. The previous research we built our expectations on was focused on education systems without extensive tracking such as the US (Staff et al., 2010) or the UK (Yates et al., 2011). Based on a typological clustering of personality into resilient and non-resilient types, we found that a resilient personality partly protects youth against becoming long-term NEET. Moreover, we found that being resilient decreases the NEET risk more strongly for youth from a disadvantageous socioeconomic background than for youth from an advantageous socioeconomic background. The protecting effect of resilience we found is about the same size as the effect for growing up in rented housing or having parents who are long-term unemployed. Hence, if youth, especially low social class youth, lack this resilient personality trait, the chance to become long-term NEET might become a real possibility for them. Lastly, social class was partly mediated via education. In fact, one fourth of the total association of lower social class background were due to the educational track pupils are sorted in. Yet, we did not find this for personality or aspirational alignment.

Recent research about technological change rang the alarm bells of social scientists and policymakers alike. Their fear is that soon artificial intelligence and advanced robotics will replace human labor and cause mass unemployment and societal polarization. However, no research has yet been conducted on how automation risks might affect the school-to-work transition. In **Chapter 4**, my co-authors and I have investigated the role of such automation risks for the early careers of graduates from Dutch vocational training. We studied two outcomes, the type of VET-to-work trajectory, including NEET trajectories, as well as income. We found four VET-to-work trajectories, including one long-term NEET trajectory. However, the likelihood of following this NEET trajectory was not higher for graduates from VET programs with a high automation risk than for graduates from VET programs with a low automation risk. In fact, we did not find any evidence that automation risks play a role in the sorting of young vocationally educated graduates into any school-to-work trajectory. Regarding wages, we found that starting wages are lower for graduates from a vocational training program with a high automation risk. The fact that we found an association of automation risk and wages but not with the NEET risk suggests that automation risk does not in itself lead to problematic school-to-work transitions.

One group often mentioned in NEET research are young mothers. Young mothers might struggle to combine motherhood with the challenges of the school-to-work transition. In **Chapter 5**, I therefore turned to the role of young mother's access to formal and informal childcare and their probability to become NEET and leave NEET. Together with my co-authors, I found that access to social support from partners and grandparents is important to young mothers in the Netherlands. Specifically, we found that having grandparents live nearby is correlated with a lower risk to become and stay NEET. Furthermore, we found that overall, the availability of formal childcare is not strongly related to young mother's NEET risks. However, in cases there are no grandparents around to help, young mothers do indeed rely on formal childcare and vice versa the role of grandparents is strongest when no childcare facilities are around.

6.2 What do the findings mean?

The presented chapters have largely confirmed our beliefs that also in the Netherlands, a country with a well-functioning transition system and strong institutional linkages, some youths fall through the cracks. While their peers successfully move from school to work or to higher education, they become long-term NEET. In the previous chapters, I have theorized and speculated about different reasons, why youths would become disengaged from the labor market and education system in such a way. I had suspected that because educational credentials are so important in the Netherlands, youths without any such credentials–particularly early school-leavers–might be at risk to become NEET and long-term NEET. **Chapter 2** provides some evidence for this, and more. Parental education and economic status, youth's immigration background, and gender are all correlated with a higher risk to become NEET. In **Chapter 3**, I added personality and aspiration and found that youth who have a set of personality traits that constitute a resilient personality are more successful to make the school-to-work transition. Moreover, resilience can partly alleviate the association between social class and becoming NEET. However, contrary to previous research, the alignment of youth's aspirations does not play a role in becoming NEET or not. In **Chapter 4**, I have then asked whether automation risks would play a role in sorting Dutch VET graduates into a long-term NEET trajectory. While automation risk is correlated with lower starting wages, it does not explain sorting into a possible problematic school-to-work trajectory. Lastly, in **Chapter 5** I turned to young mothers and their social support networks and showed that a tightly knit social support network is a key asset of young mothers to stay active on the labor market and education.

One might ask what this means for young people? Does the presented evidence hold up against all-too-common wisdom of lazy youth who simply make bad choices? The answer to this question is not easy. The debates around the interplay of agency or structure, and individual choice or deterministic social origin are long-standing in sociology. Hence, it escapes the scope of this thesis to settle it. Still, it is worthwhile to view the results of this thesis in this perspective. Different theorists suggested that the life course, and the transition to adulthood, have become more individualized (Beck, 1992; Giddens, 1991). The argument was that modernity brought with it a shift from deterministic career trajectories, based on social class background and gender, to more individualized, but also riskier and uncertain, early careers. In such a context, agency and choice would become more important. However, agency is not a clear-cut concept. In fact, it is not even clear if agency is restricted to personality, aspirations, and motivation, or if agency is about resources and the perception of resources (Hitlin & Johnson, 2015). Disentangling agency from structure is difficult as well because agency is likely influenced by structure (Schoon & Lyons-Amos, 2017; Shanahan, 2000). In the light of this, the results of this thesis provide some pieces to the puzzle. For example, by showing that resilience can help to avoid becoming NEET in **Chapter 3** or by showing that access to formal and informal childcare matters for young mothers in **Chapter 5**. Yet, questions remain on the interplay of agency and structure, especially regarding policy implications. For childcare, increasing its accessibility and acceptance seem to be a straight-forward policy recommendation. However, should–and could–we teach some type of resilience classes to disadvantaged youth? Aside from the fact that it is unclear how malleable things like personality really are (most recently, see Stieger et al., 2021), shouldn't we create policies that make disadvantaged youth less disadvantaged in the first place? For example, qualitative research on young mothers shows how they already use different coping strategies (agency) and how many of the barriers they face are in fact structural (for example, low flexibility and strict required attendance in school) (Keinemans et al., 2018; Sniekers & van den Brink, 2019). Here, more research is needed.

6.3 What issues remain, and where do we need better evidence?

In conducting this research, I have provided some pieces to the puzzle of NEET in the Netherlands. In particular, I have presented a more holistic perspective using longitudinal typologies from sequence analyses. While this constitutes a significant step-forward from cross-sectional analysis, the analyses presented are not free from limitations. Some of these open issues are presented in the following section.

While the concept of NEET is concerned with working vs. not working, and studying vs. not studying, it might not be enough to truly describe the situation of young people today. What is certainly missing, is the quality of the job or the education and training. Flexible jobs without a long-term perspective might be as big a challenge for labor market integration, as might be training participation that does not lead to better employment chances. More evidence is needed in this regard, especially for the lowest-qualified and early school-leavers. Future research should therefore also revisit the situation of early school-leavers. Previous research in the Netherlands (e.g., Traag, 2012) has shown that early school-leaving is correlated with similar variables as NEET, namely family background, human capital, cognitive skills, and personality. However, even if we know how to prevent early school-leaving, some youths will still leave school early or with no diploma. Currently, we lack the know-how to best deal with such cases. Evidence from Germany shows how pre-vocational training for low-achieving school-leavers in Germany can improve their chances of starting an apprenticeship

(Holtmann et al., 2017). In the Netherlands, an equivalent 'second chance' scheme is found in some local 'Pre-MBO' pilot projects and the MBO at level 1 so called 'entreeopleidingen' (Inspectorate of Education, 2018).

Another way to progress on the current thesis is by focusing on identifying causal effects. The methods used in this thesis, most notably sequence analysis, do not allow for causal interpretation. While descriptive evidence is important, especially to 'establish the phenomenon' as argued in **Chapter 1**, causal evidence is preferable to provide good policy advice. Such evidence can come from the use of natural experiments with observational data, or from field experiments. Natural experiments can yield evidence for policy changes, such as the introduction of the *Wet Investeren in Jongeren (Work Investment Act for Young Individuals)* (e.g., Cammeraat et al., 2017). Field experiments are important for interventions, like buddy and mentoring programs, or workshops. If such programs are rolled-out without careful assessment of their effects, there is a real danger that they can cause more harm than good (e.g., McCord, 2003). Furthermore, programs must be assessed for scaling. Meaning, to what extent a small-scale, local program, curated and facilitated by scholars, can be scaled-up to a nation-wide program. This is crucial, especially with interventions that mostly rely on the human factor, like a buddy or mentor. In the controlled setting of the initial study, researchers can hand-pick highly motivated and skilled administrators. When an intervention is scaled up, this selection is no longer supervised by the researchers and subject to the general supply of professional administrators, including less motivated and lower skilled ones (see Al-Ubaydli et al., 2017). In the impact paragraph, I will present such an approach to test the effectiveness of an intervention.

As argued in **Chapter 3**, resilience is a key-asset of young people during the school-to-work transition. However, there is still an ongoing debate about what resilience is. While we operationalized resilience as a personality type Robins et al. (1996), others have argued that resilience represents a set of competences and resources to achieve goals in the face of adversity (e.g., Schoon & Bynner, 2003). While the former personality-based concept, might suffer from forcing resilience into the 'individual trait' corner, the latter tries to include social-ecological factors but suffers from conceptual vagueness. The former approach can be traced back to Block & Block (1980). Here, *ego resilience* is understood as "the tendency to respond flexibly rather than rigidly to changing situational demand" (Robins et al., 1996, p. 159). The latter approach was influenced by Masten (2001) and earlier work on childhood development and among others picked-up by Ungar (2008): "In the context of exposure to significant adversity, whether psychological, environmental, or both, resilience is both the capacity of individuals to navigate their way to health-sustaining resources, including opportunities to experience feelings of well-being, and a condition of the individual's family, community and culture to provide these health resources and experiences in culturally meaningful ways." By combining different classical sociological and psychological factors into one latent factor of resilience, the conceptual lines between them are blurred. It is unclear how conceptually different, and therefore useful, such an operationalization would be compared to directly measuring social norms, social capital, personality, ability and things like aspirations and parental support. More importantly, it remains unclear whether resilience should be understood as the means to an end or the end itself.

In **Chapter 4**, we used occupation data matched to VET programs to estimate the effect of automation risk during the early career of VET graduates. Future research could use data from curricula of VET programs directly. Qualification dossiers ("Kwalificatiedossier") from the Foundation for Cooperation on Vocational Education, Training and the Labor Market (Samenwerkingsorganisatie Beroepsonderwijs Bedrijfsleven, SBB) include very detailed information on the skills and tasks that a graduate from a certain program has learned and should be able to perform upon graduating. These could be coded into different categories, for example manual/cognitive or routine/non-routine. In addition, the descriptions could be mined for other aspects of the program, such as whether organization, planning, and social skills are needed, or whether and how much autonomy or creativity is asked from graduates.

For prospective research, register data as used in this thesis are preferable over survey data. However, sometimes retrospective data are needed. For example, I was not able to compare different cohorts, because the main datasets in the Social Statistical Database only start in 1999 or later. A retrospective life-course survey would enable us to compare the school-to-work transitions of older cohorts with those of today. This would help us to establish long-term societal trends like Brzinsky-Fay (2022) did for Germany using data from the National Education Panel Study (NEPS). His results show that while younger cohorts are more likely to experience at least one month of NEET, they are not more likely to follow 'problematic' NEET trajectories.

The situation of immigrants and children of immigrants is still not well understood and there are few studies of immigrant children's school-to-work transition in the Netherlands (ROA, 2016; however, see Wessling & Meng, 2021). In this thesis we show some evidence that immigration background is correlated with having a problematic school-to-work transition, but results are sometimes mixed. One of the issues here is that in this thesis immigration background mainly serves as control variable, which does not allow for a good interpretation of the underlying mechanism and should not be assigned too much interpretation (Hünermund & Louw, 2020). However, there is strong field experimental evidence of ethnic discrimination on the Dutch labor market for young people with an immigration background (Thijssen et al., 2021). Still, more specific, and especially more longitudinal research is needed that goes beyond what we know about immigrant youth in education or their immediate entry into the labor market. While there are many ways to possibly study the effect of immigration background on labor market entry, one especially promising avenue is to isolate parts of the mechanism well with the use of innovative data source such as measurements of foreign accents in speech (Dollmann et al., 2020; Schmaus & Kristen, 2021).

The roles of the local labor market and other regional effects for successful school-to-work transitions are not well-understood. However, little such research exists. One possible regional effect might be the industrial heritage of the eastern coal mining district in Limburg in the Netherlands. The closure of the coal mines and the resulting economic downturn might have created long-lasting effects. Because mining was so common (some municipalities had more than two-thirds of their male population work in the mine), the consequences of the closures were grave. Nearly everybody living in this region today is familiar with the narrative of unemployment in parents' or grandparents' biography (Luyten, 2015). Such concentrated joblessness might change social norms (Wilson, 1997). Young people growing up in these communities lack the role model of (higher status) working adults and might be less inclined to invest in education because they do not see the benefits of it (Ainsworth, 2002). They also have less access to diverse information on job opportunities (van der Klaauw & van Ours, 2003). This argumentation is in line with previous research which argues that the negative effects of neighborhood poverty on economic outcomes mainly work through accumulated childhood exposure (Chetty & Hendren, 2018; Sharkey & Faber, 2014) and that having lived in a deprived neighborhood has substantial lingering effects on later income (Miltenburg & van der Meer, 2018).

I have previously encouraged researchers and policymakers to refrain from labelling young people who *become* NEET during their school-to-work transition, as "the NEETs". Such a label suggests homogeneity and some sort of group identity. Yet, there are online communities, such as *reddit.com/r/NEET*, whose members embrace NEET as a label. In these online communities, discussions often concern coping with anxiety and depression, but also poverty and welfare or the lack motivation. Members celebrate each other's success when finding a job but also talk about ways to get social benefits, so-called *NEETbux.* While to the members, these communities might be a valid source of help and emotional support, it should not be underestimated how self-stigmatizing these echo-chambers can be. Figure 6.1 shows a word cloud of the posts in an online community since 2016. While the most common topics revolve around employment and social connections, some discussions revolve around mental health and feelings of anger and anxiety. One possible avenue for future research is content analysis of such online communities or qualitative interviews with young people who define themselves as NEET to better understand their situation and their acceptance of that label. Indeed, the labelling by policymakers as "the NEETs" might have become a self-fulfilling prophecy.

Figure 6.1: Word cloud from posts in an online NEET community. "NEET", "NEETs" and common stop words are omitted to increase visibility of other words. Source: reddit.com/r/NEET, own calculations.

6.4 How to continue?

The main quarrels of NEET research, that is, the concept and operationalization itself, partly remain unresolved. While re-inventing the NEET concept was never the aim of this thesis, I will use this section to reflect on it and speculate on its future. While longitudinal analyses are necessary, the usefulness of an analysis of "longitudinal NEET" compared to "longitudinal unemployment/joblessness/inactivity/educational drop-out" is less obvious. NEET is lumping them all together while at the same time promising to better capture the situation of affected youths. While this is partly true, it is not the concept that better captures the situation of unemployed, economically inactive, but the data. Only good data can capture the realities of youth who are struggling with their school-to-work transition. For that, the register data used throughout this thesis reaches its limits. Using it, I could not differentiate training participation or the actual (subjective) reason of being NEET. While this is possible using surveys, these data will have other shortcomings. Hence, more matching of survey to register data is needed. This could enable researchers to use different status definitions to study different mechanisms. Sequence analysis has proved to be a useful tool to do that, because the number of states in the alphabet can be easily extended. Moreover, multichannel sequence analysis could prove a promising way to separately classify the activities on the labor market and in education or family formation (e.g., Aisenbrey & Fasang, 2017), thereby more closely doing justice to the life course paradigm where processes in different life domains are expected to influence each other. Once we can accurately measure and describe the different states young people pass through during their school-to-work transition, and separately analyze labor market and educational activity, NEET as a concept (in contrast to NEET as a variable or state) might no longer be necessary.

Impact paragraph

The research presented in this thesis aimed to further understand the process of becoming NEET in the Netherlands. The results have implications for youth, NEET, and school-to-work transition policy and should therefore be of concern to researchers and policymakers alike.

The most important result is that few young people in the Netherlands become and stay NEET for the long term. However, those who do, are especially negatively selected, and stay NEET for a long time. Among others, early school leaving is an important predictor to become NEET. Hence, further attention should be paid to early school-leavers. Different policy changes have already reduced the number of early school-leavers. Between 2010 and 2020, the number of 18–24-year-olds without a starting qualification sank from 10% to 7% (Statistics Netherlands, 2021b). However, in recent years the number of yearly new early school-leavers has stagnated and between 2017 and 2018 it rose from 23,774 to 25,574. This is partly due to the creation of the regional registration and coordination points (RMC) and tighter monitoring. So, what further steps should policymakers take? The government recently issued the goal to further reduce the number of yearly new early school-leavers to 20,000 by 2024. This is to be achieved, among else, by further strengthening the role of the RMCs and giving them the role of a networking broker, not only between early school-leavers and schools but also for finding work. This seems promising. However, those in charge of implementing the plans raised concerns about setting an absolute number as a goal, and criticized the plan for the lack of additional funding to the RMCs while increasing their workload, the lack of attention to young people over 23, and the lack of a plan for those who despite all these efforts still can't or won't attain a diploma [1]. Trying to reduce this number without

[1] see the discussion on www.internetconsultatie.nl/regelingregionaleaanpakvsv

thinking about how to deal with those who are not able to attain the necessary qualifications to enter the labor market is short-sighted. Society should not stigmatize these young people. Instead, more direct matching of low-skilled youth to employers and individual prevention and assistance should be the goal. Giving the RMCs this new task might be a step in the right direction. Another way to achieve this might be to train those in labor market brokering and mentoring who already are in contact with the target group, e.g., social workers and local NGOs. One reason why more direct matching paired with individual guidance and counseling is needed, is the policy shift from a classical welfare state to the participation society. In 2013, Willem-Alexander, King of the Netherlands, said in his first throne speech: "It is undeniable that in our current network- and information society people are more empowered and independent than in the past. Combined with the need to reduce the deficit of the government, this leads to the classic welfare state slowly but surely changing into a participation society. Everyone who can is asked to take responsibility for his or her own life and environment". However, it has been suggested that the participation society asks too much of its citizens (WRR, 2017). Young people must navigate the institutional bureaucracy nexus of schools, employers, their municipality (responsible for social assistance), and the employee insurance agency. Those who lack the support to do so, should be given more support. This could for example happen in the form of a buddy or coaching program.

In **Chapter 4**, we showed that the risk of automation is correlated with lower starting wages at the labor market entrance of vocational education and training graduates. Although we show no correlation of automation risk and the likelihood to become NEET, more research is needed. It is likely that the hypothesized effects of automation are yet to unfold and that future studies come to different conclusions. Policymakers should keep in mind that the effect of automation and technological change is different across educational fields. To some degree, future proofing the curricula of VET programs is already on the agenda of those responsible for the vocational education and training curricula. For example, the *Foundation for Cooperation on Vocational Education, Training and the Labour Market* (Samenwerkingsorganisatie Beroepsonderwijs Bedrijfsleven, SBB) clearly communicates their attention to robotization on their website. However, what is missing is a wider effort to address automation and robotization in the curricula directly. While curricula are already designed in cooperation with employer representatives, an external task force of automation and robotization experts should be consulted to future proof the VET programs.

Another aspect to address here are young mothers. If, as suggested in **Chapter 5**, young mothers must rely on their grandparents and other members of their social network to take care of their children, then it should be questioned whether society is doing enough for those without such tight support networks. One point of failure to address might be schools and other educational institutions. One approach might be the introduction of maternal leave for students in the vocational training and at university. Some MBO institutions are also starting to offer specific programs for young mothers, which include classes that end in the afternoon and encourage networking among young mothers (for example www.davinci.nl/jongemoederklas). However, often, these classes are limited to the lower levels of vocational education, specifically MBO1 and 2, of which MBO1 is not considered a full education in the sense of a starting qualification. Clearly, a broader initiative is needed that enables young mothers to also study at the higher levels. Furthermore, it is necessary to reduce both the stigma against young motherhood in education while at the same time addressing the stigma of mothers against formal childcare and its quality. However, as social norms are not easily changed, a more direct policy change would be to stop making childcare subsidies contingent on economic activity.

To conclude. Given the large social and economic costs attached to being long-term NEET, society needs policies that work. During the research of this thesis, I came across many different social organizations that offer programs for vulnerable young people. However, what is needed, is evidence that such programs work. For this, more field experimental research is needed. Therefore, a proposal for an intervention study to test the effectiveness of a personal guidance program is laid out in the appendix.

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Appendix

A Appendix to Chapter 3

A.1 Sample preparation

The following figure shows the data handling steps to prepare the sequence analysis. First, the whole sample and their activity between January 2001 to December 2018 is shown. Clearly visible is a regular "teeth" pattern in activity, which disappears after we exclude every observation from August. We do so to not mistaken regularities in the administration for real school-leaving. We then exclude episodes with more than 10% missing episodes and align on the first episode after school-leaving. After that step, the horizontal axis changes from calendar time (2001 to 2018) to process time (years after school-leaving)

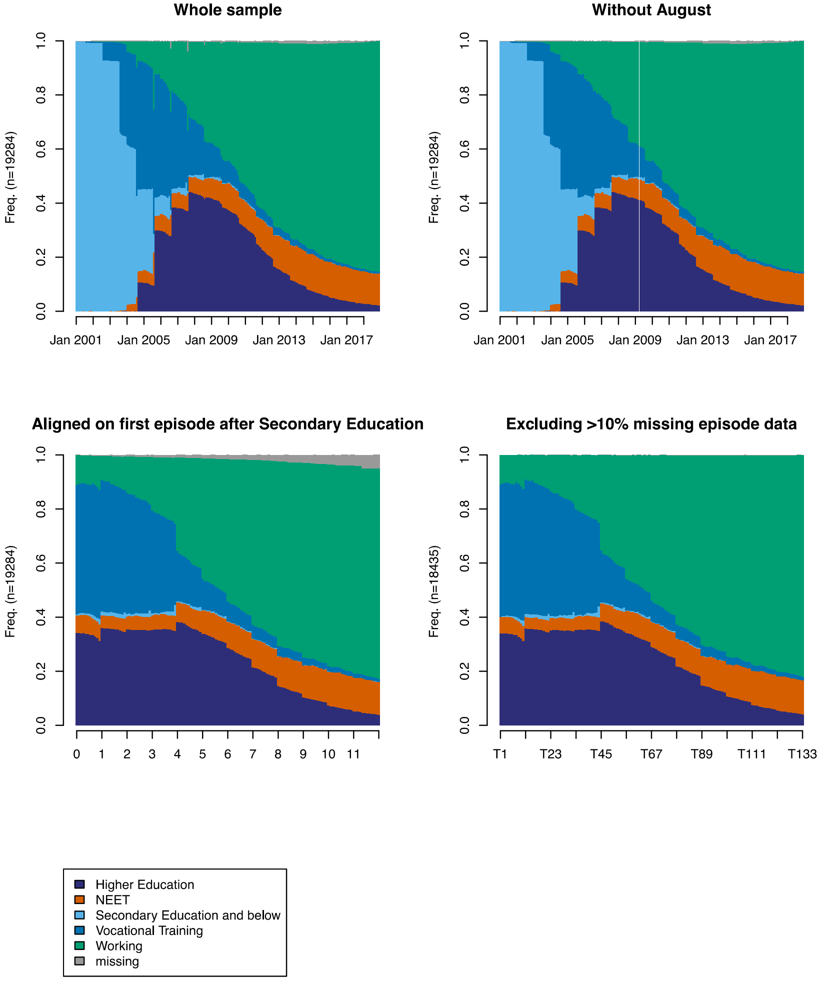


Figure A.1.1: Status proportion plot to visualize the steps taken in the preparation of the final sample. Source: Statistics Netherlands, own calculations.

A.2 Cost setting, linkage functions, cluster solutions, and cluster trees

Table A.2.1: Overview of different cluster solutions by cost setting structures and cluster linkage functions.

Cost setting	Linkage	Long-term NEET cluster	Clusters	Months NEET	N	%
OM(1,2)/ LCS	Ward's	Yes	Employment	9.66	7,770	42.15
			Further Education	6.52	9,231	50.07
			Long-term NEET	96.57	1,434	7.78
	Complete	Yes	Employment/ Education	7.70	16,943	91.91
			Long-term NEET	95.98	1,492	8.09
	Average	Yes	Employment/ Education	8.90	17,309	93.89
			Long-term NEET	106.32	1,126	6.11
OMspell	Ward's	No				
	Complete	No long-term NEET				
	Average	No, singularities				
SVRspell	Ward's	No, singularities				
	Complete	No, singularities				
	Average	No, singularities				

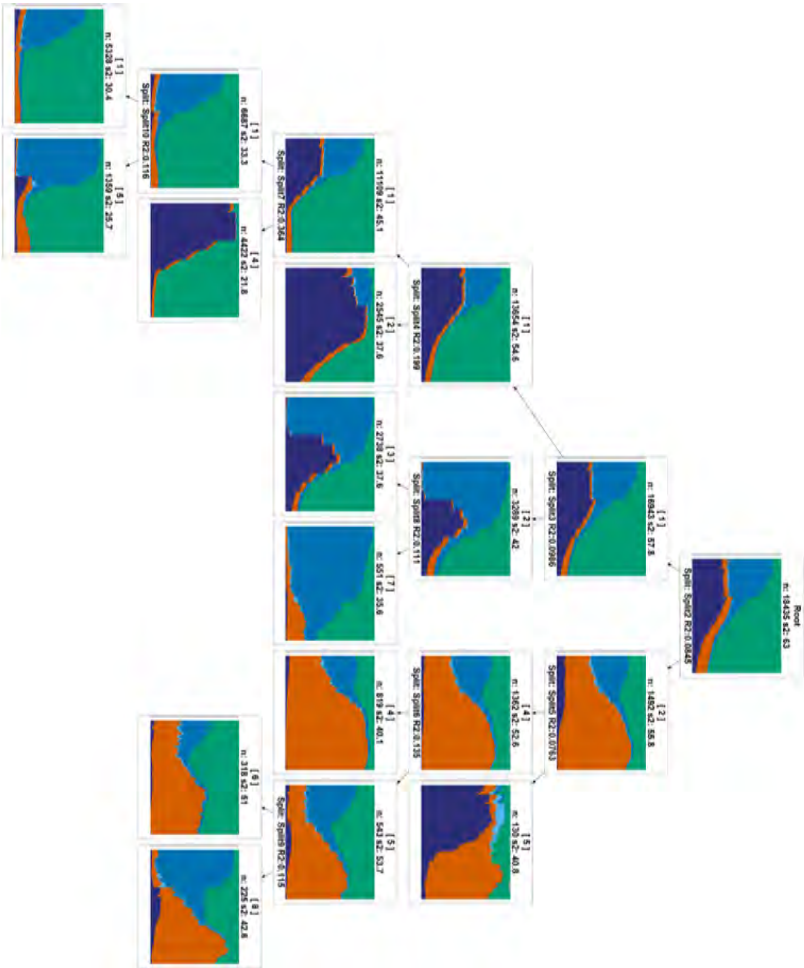


Figure A.2.1: Cluster tree, complete linkage function, OM(1,2)/LCS

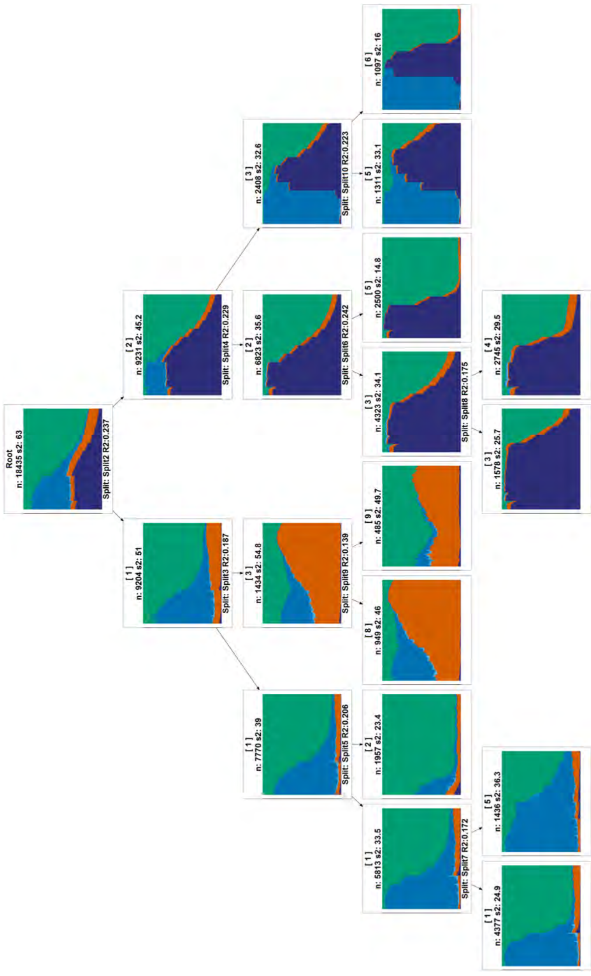


Figure A.2.2: Cluster tree, Ward's linkage function, OM(1,2)/LCS

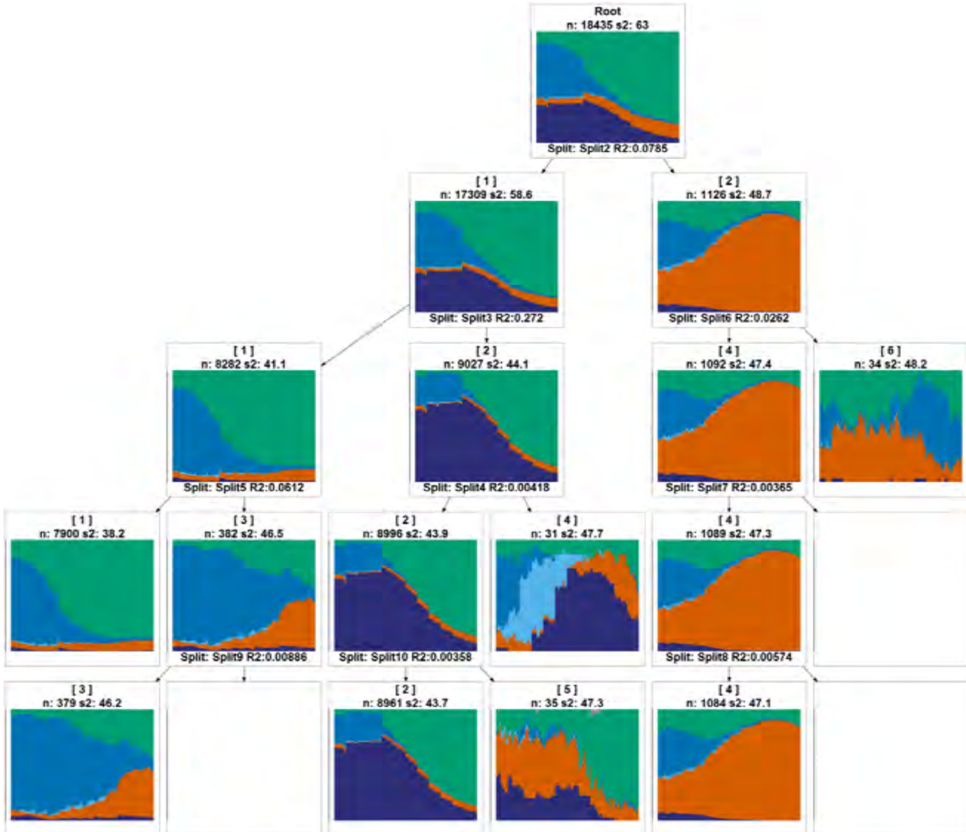


Figure A.2.3: Cluster tree, Average linkage function, OM(1,2)/LCS

A.3 Missing data

Variable	Missing observations	Percent
single_parent	2092	11.3
female	< 10	
pared	2419	13.1
punemp	3011	16.3
hhincome_ssb1k	1804	9.8
homeown	1761	9.6
educ	36	0.2
age	< 10	
emost	3632	19.7
extra	3496	19.0
consc	3422	18.6
agree	3690	20.0
auton	3635	19.7
gbageneratie	< 10	
rctot	1150	6.2

A.4 Pupil's expectation and track placement

Table A.4.1: Cross tabulation of pupil's educational expectation and their educational track in 1999

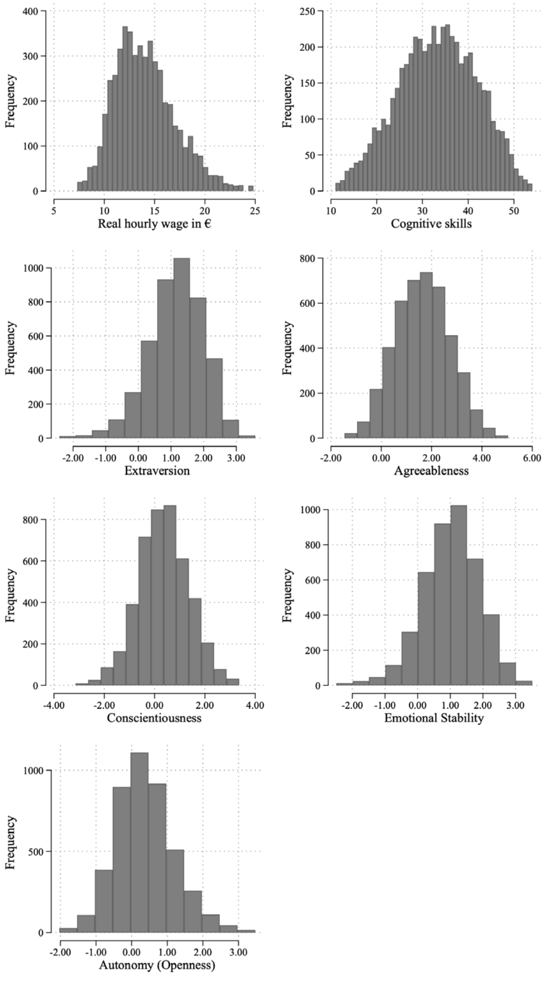
	Pupil's educational expectation:			
Track in 1999	Academic	Vocational	Don't know	Total
General	2,632	88	2,037	4,757
	55.33	1.85	42.8	100
Vocational	1,787	1,243	3,166	6,196
	28.8	20.1	51.1	100
Total	4,419	1,331	5,203	10,953
	40.35	12.15	47.5	100

Table A.4.2: Cross tabulation of pupil's track before leaving school and their educational track in 1999.

	Track in 1999:		
Track before leaving school	General	Vocational	Total
Practical	99	618	717
	13.81	86.19	100
VMBO	439	3,624	4,063
	10.8	89.2	100
HAVO	1,961	986	2,947
	66.54	33.46	100
VWO	2,075	134	2,209
	93.93	6.07	100
Other (assigned)	183	834	1,017
	17.99	82.01	100
Total	4,757	6,196	10,953
	43.43	56.57	100

B Appendix to Chapter 4

B.1 Data



Note: Frequencies < 10 not shown

Figure B.1.1: Histograms

B.2 Sequence analysis

Table B.2.1: Ranked cluster quality statistics of four clustering methods and ten partitions

		PBC	HG	HGSD	ASWw	CH	CHsq	HC	Total
Method	**Partition**	**Value**	**Value**	**Value**	**Value**	**Value**	**Value**	**Value**	**Rank**
Ward	2	0.58	0.72	0.71	0.51	2264	4269	0.15	8
	3	0.46	0.60	0.60	0.37	1745	2975	0.19	32
	4	0.50	0.68	0.67	0.36	1482	2629	0.16	34
	5	0.56	0.79	0.79	0.39	1374	2993	0.10	22
	6	0.58	0.85	0.85	0.39	1227	2819	0.07	12
	7	0.59	0.88	0.87	0.40	1102	2674	0.06	7
	8	0.57	0.88	0.88	0.35	1016	2429	0.06	23
	9	0.58	0.89	0.89	0.35	939	2371	0.05	22
	10	0.57	0.90	0.90	0.36	878	2204	0.05	20
Average	2	0.36	0.82	0.82	0.52	325	683	0.20	28
	3	0.64	0.86	0.85	0.49	596	1487	0.08	14
	4	0.64	0.86	0.85	0.48	400	997	0.08	25
	5	0.64	0.85	0.85	0.41	314	785	0.08	27
	6	0.64	0.85	0.85	0.38	271	675	0.08	31
	7	0.64	0.85	0.85	0.37	227	565	0.08	34
	8	0.72	0.87	0.87	0.50	607	1580	0.06	5
	9	0.74	0.91	0.91	0.51	605	1659	0.04	1
	10	0.74	0.91	0.91	0.51	557	1564	0.04	3
PAM	2	0.59	0.72	0.72	0.51	2328	4358	0.14	17
	3	0.71	0.87	0.87	0.55	1734	3928	0.06	5
	4	0.65	0.84	0.83	0.48	1527	3427	0.08	25
	5	0.70	0.91	0.91	0.49	1435	3757	0.04	11
	6	0.68	0.92	0.92	0.47	1274	3346	0.04	17
	7	0.68	0.92	0.92	0.46	1135	3079	0.04	20
	8	0.67	0.93	0.93	0.43	1051	2927	0.03	26
	9	0.67	0.93	0.92	0.43	968	2748	0.04	31
	10	0.67	0.94	0.93	0.43	913	2737	0.03	29
Complete	2	0.14	0.50	0.50	0.34	92	140	0.43	36
	3	0.40	0.74	0.74	0.37	235	486	0.22	35
	4	0.71	0.86	0.86	0.47	847	2212	0.06	2
	5	0.71	0.86	0.86	0.43	706	1866	0.06	6
	6	0.71	0.86	0.86	0.42	573	1517	0.06	11
	7	0.71	0.86	0.86	0.41	489	1299	0.06	14
	8	0.73	0.88	0.87	0.40	445	1206	0.05	11
	9	0.73	0.88	0.87	0.39	398	1085	0.05	17
	10	0.73	0.88	0.88	0.39	376	1042	0.05	18

B.3 Correlations of automation risk measures

		Frey & Osborne			Somers & Fouarge		
		"Computerization"			"Share less time"		
		All	50%	First	All	50%	First
		1	2	3	4	5	6
FO	1	1.00					
	2	0.97	1.00				
	3	0.87	0.89	1.00			
SF	4	0.78	0.74	0.71	1.00		
	5	0.68	0.70	0.67	0.95	1.00	
	6	0.51	0.53	0.64	0.79	0.84	1.00

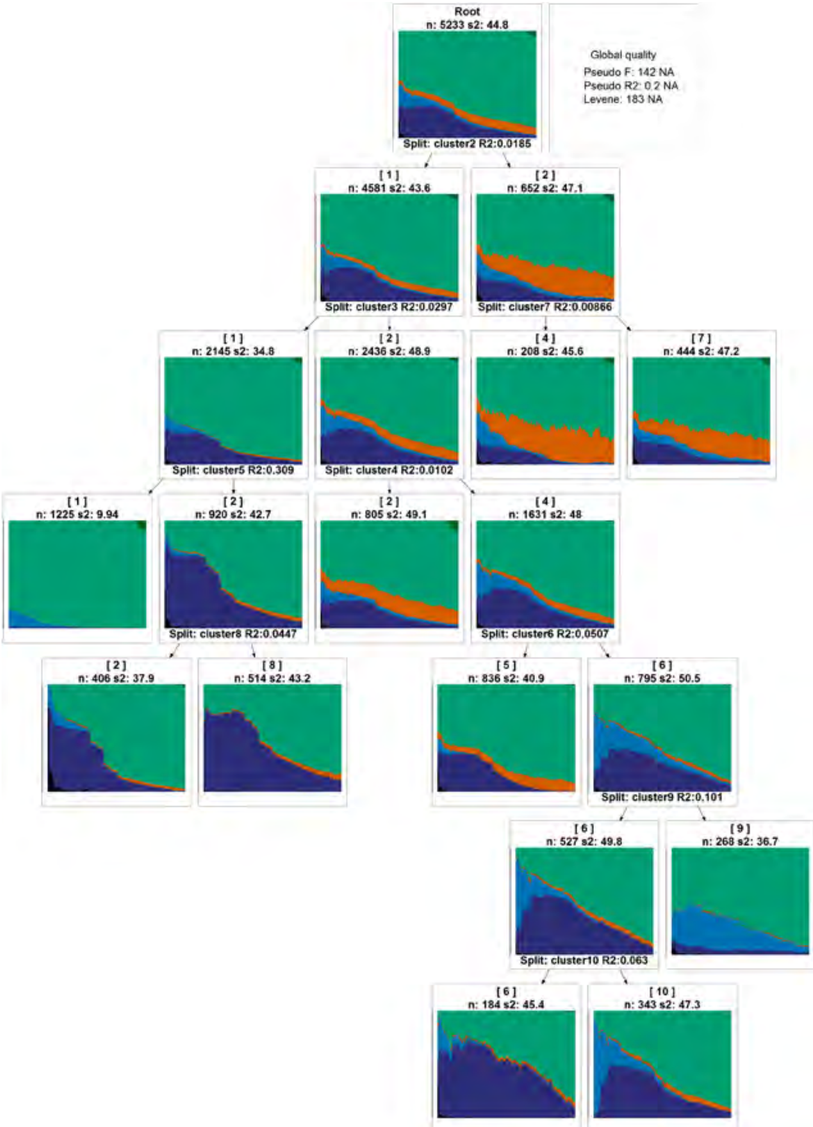


Figure B.2.1: Cluster tree, Ward's linkage function, OM(1,2)/LC

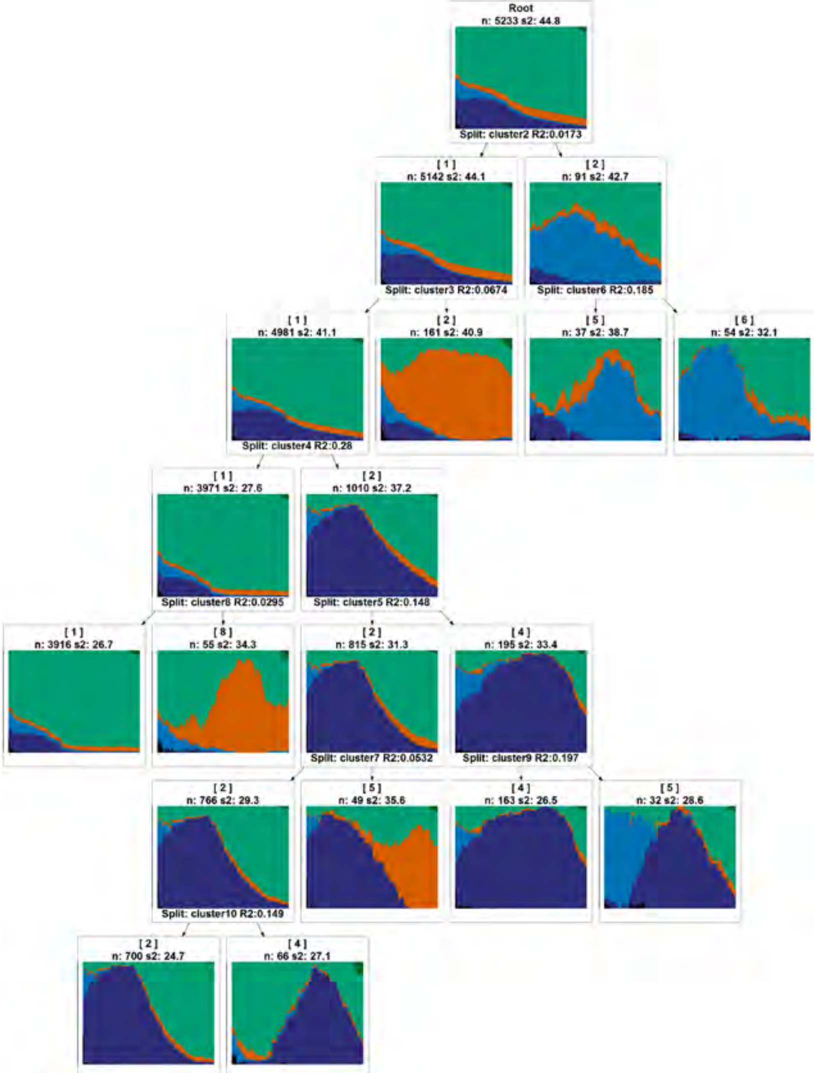


Figure B.2.2: Cluster tree, complete linkage function, OM(1,2)/LCS

B.4 Alternative specifications to Figure 4.5

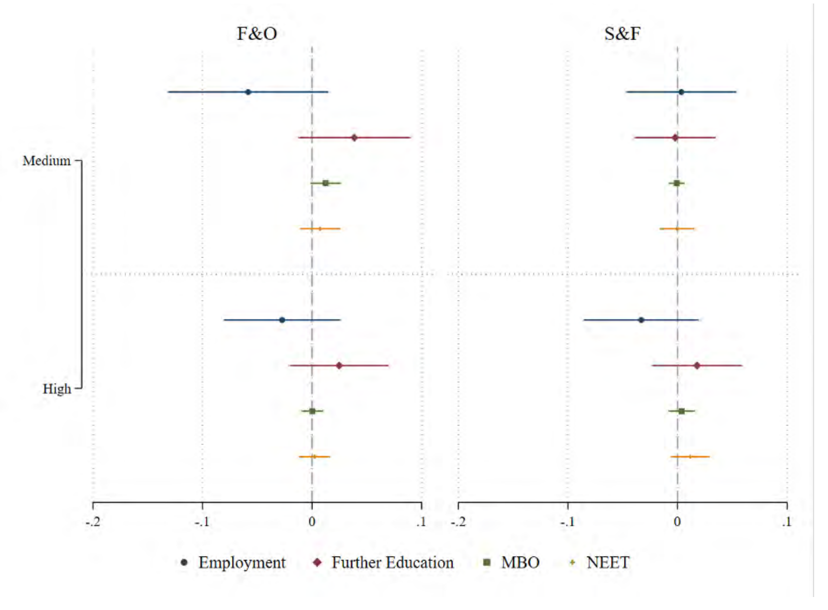


Figure B.4.1: Average marginal effects for post-VET trajectories given different levels of automation risk (terciles).

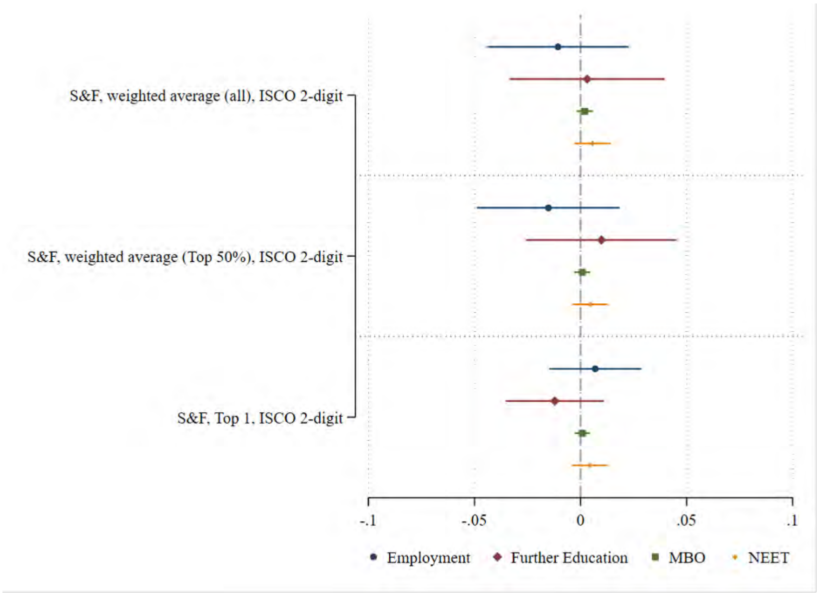


Figure B.4.2: Average marginal effects to follow each early career trajectory for Somers & Fouarge indicators of automation risk of MBO programs. Controlled for occupational linkage; level-field-clustered standard errors.

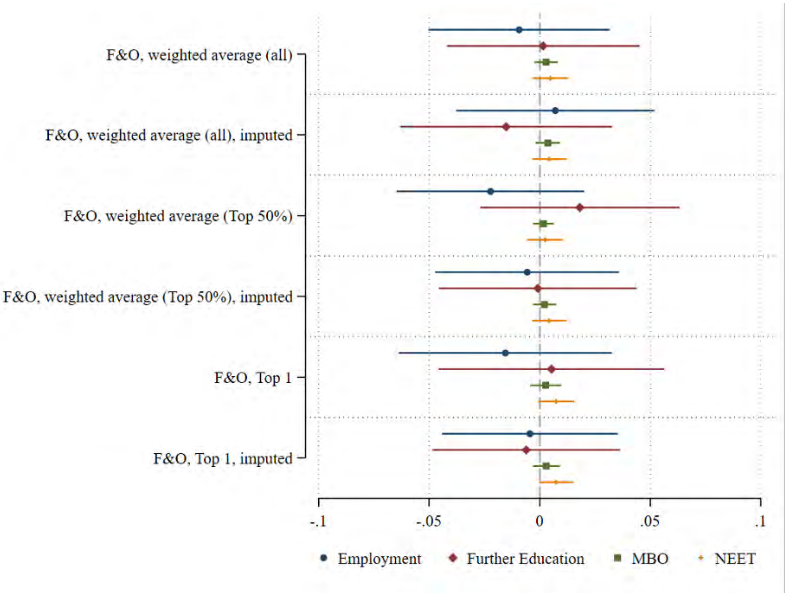


Figure B.4.3: Average marginal effects to follow each early career trajectory for Frey & Osborne indicators of automation risk of MBO programs. Controlled for occupational linkage; level-field-clustered standard errors.

B.5 Additional tables: Multinomial logistic regressions

Table B.5.1: Multinomial logistic regression of trajectories, F&O dummy (mean-split)

	Further Education		MBO		NEET	
	b	SE	b	SE	b	SE
Automation risk (F&O), ref. cat. Low						
High	1.16	0.18	1.33	0.44	1.45	0.42
Occupational linkage	0.98*	0.01	1.01	0.01	1.03*	0.02
Field of diploma, ref.cat.: Blue Collar						
Services	2.13***	0.38	0.35***	0.14	1.18	0.40
Gender, ref.cat.: Male						
Female	0.65***	0.10	1.40	0.50	3.01***	0.94
Immigration backgr., ref.cat. No						
Migrant	1.81***	0.28	1.37	0.66	1.98***	0.45
Level, ref. cat.: MBO3						
MBO4	3.84***	0.95	0.67	0.22	0.93	0.28
Personality and Cognitive Skills						
Cognitive skills	1.09	0.06	0.94	0.15	1.28**	0.15
Emotional Stability	1.07	0.05	1.28	0.25	0.82*	0.10
Extraversion	0.85***	0.04	0.74*	0.12	0.79**	0.08
Conscientiousness	0.93	0.05	0.85	0.13	1.08	0.12
Agreeableness	1.01	0.06	0.90	0.14	0.93	0.13
Autonomy	1.21***	0.06	1.08	0.16	0.91	0.09
Parental education, ref. cat. Low						
Secondary	1.12	0.16	1.42	0.46	0.80	0.17
Tertiary	1.83***	0.27	1.47	0.43	1.02	0.28
Housing ownership, ref. cat. Owned						
Rented	0.99	0.10	0.88	0.25	1.65**	0.37
Parental household income (log)	0.95	0.10	0.58*	0.18	0.63***	0.08
N	3,250					
Pseudo R2	0.097					
BIC	4397.3					

Coefficients represent relative risk ratios; * p <0.1 ** p <0.05 *** p <0.01. Source: Statistics Netherlands, own calculations.

Table B.5.2: Multinomial logistic regression of trajectories, S&F dummy (mean-split)

	Further Education		MBO		NEET	
	b	SE	b	SE	b	SE
Automation risk (S&F), ref. cat. Low						
High	1.10	0.13	0.91	0.26	1.74**	0.47
Occupational linkage	0.97**	0.01	1.01	0.01	1.03**	0.01
Field of diploma, ref.cat.: Blue Collar						
Services	2.04***	0.32	0.31***	0.12	1.09	0.34
Gender, ref.cat.: Male						
Female	0.66***	0.10	1.34	0.50	3.42***	1.04
Immigration backgr., ref.cat. No						
Migrant	1.82***	0.27	1.42	0.67	1.93***	0.45
Level, ref. cat.: MBO3						
MBO4	3.73***	0.92	0.63	0.20	0.90	0.26
Personality and Cognitive Skills						
Cognitive skills	1.09	0.06	0.95	0.15	1.26**	0.15
Emotional stability	1.07	0.06	1.28	0.25	0.81*	0.10
Extraversion	0.86***	0.04	0.74*	0.12	0.79**	0.09
Conscientiousness	0.93	0.05	0.85	0.13	1.08	0.12
Agreeableness	1.01	0.06	0.90	0.14	0.93	0.13
Autonomy	1.21***	0.06	1.07	0.15	0.91	0.09
Secondary	1.12	0.16	1.43	0.46	0.79	0.16
Tertiary	1.81***	0.27	1.47	0.43	1.00	0.28
Rented	0.99	0.10	0.88	0.25	1.64**	0.37
Parental household income (log)	0.95	0.10	0.58*	0.17	0.63***	0.08
N	3,250					
Pseudo R2	0.098					
BIC	4395.6					

Coefficients represent relative risk ratios; * p <0.1 ** p <0.05 *** p <0.01. Source: Statistics Netherlands, own calculations.

Table B.5.3: Multinomial logistic regression for moderations of automation risk (F&O) and social class: Parental education

	Further Education		MBO		NEET	
	b	SE	b	SE	b	SE
Automation risk (F&O), ref. cat. Low						
High	0.96	0.27	1.72	1.03	1.59	0.47
Parental education, ref. cat. Low						
Secondary	0.99	0.17	1.95	1.21	0.76	0.18
Tertiary	1.62***	0.23	1.35	0.78	1.45	0.45
Interaction						
High X Secondary	1.28	0.33	0.61	0.45	1.17	0.49
High X Tertiary	1.27	0.32	1.15	0.73	0.33	0.24
Personality and Cognitive Skills						
Cognitive skills	1.09*	0.06	0.94	0.15	1.26*	0.15
Emotional stability	1.07	0.05	1.29	0.25	0.82*	0.10
Extraversion	0.85***	0.04	0.74*	0.12	0.79**	0.08
Conscientiousness	0.93	0.05	0.85	0.13	1.08	0.12
Agreeableness	1.01	0.06	0.90	0.14	0.92	0.13
Autonomy	1.21***	0.06	1.08	0.16	0.91	0.09
Occupational linkage	0.98*	0.01	1.01	0.01	1.03*	0.02
Services	2.14***	0.38	0.35***	0.14	1.18	0.40
Gender, ref.cat.: Male						
Female	0.65***	0.10	1.39	0.49	3.07***	0.96
Immigration backgr., ref.cat. No						
Migrant	1.83***	0.28	1.39	0.67	2.00***	0.45
MBO4	3.85***	0.96	0.68	0.22	0.89	0.27
Rented	1.00	0.10	0.87	0.25	1.63**	0.36
Parental household income (log)	0.96	0.10	0.57*	0.18	0.62***	0.08
N	3,250					
Pseudo R2	0.098					
BIC	4391.7					

Coefficients represent relative risk ratios; * p <0.1 ** p <0.05 *** p <0.01. Source: Statistics Netherlands, own calculations.

Table B.5.4: Multinomial logistic regression for moderations of automation risk (S&F) and social class: Parental education

	Further Education		MBO		NEET	
	b	SE	b	SE	b	SE
Automation risk (S&F), ref. cat. Low						
High	0.87	0.21	1.28	0.74	1.50	0.46
Parental education, ref. cat. Low						
Secondary	0.97	0.19	2.08	1.04	0.61*	0.16
Tertiary	1.44***	0.19	1.13	0.43	1.21	0.39
Interaction						
High X Secondary	1.28	0.33	0.49	0.33	1.64	0.67
High X Tertiary	1.50*	0.35	1.48	0.72	0.67	0.40
Personality and Cognitive Skills						
Cognitive skills	1.09*	0.06	0.95	0.15	1.25*	0.15
Emotional stability	1.07	0.05	1.29	0.25	0.81*	0.10
Extraversion	0.86***	0.04	0.74*	0.12	0.79**	0.09
Conscientiousness	0.93	0.05	0.85	0.13	1.08	0.12
Agreeableness	1.01	0.06	0.89	0.14	0.93	0.13
Autonomy	1.21***	0.06	1.07	0.15	0.91	0.09
Occupational linkage	0.97**	0.01	1.01	0.01	1.03**	0.01
Services	2.06***	0.32	0.30***	0.11	1.11	0.35
Gender, ref.cat.: Male						
Female	0.66***	0.09	1.33	0.49	3.41***	1.02
Immigration backgr., ref.cat. No						
Migrant	1.84***	0.27	1.41	0.70	1.96***	0.45
Level, ref. cat.: MBO3						
MBO4	3.75***	0.94	0.65	0.19	0.88	0.26
Rented	1.00	0.10	0.88	0.26	1.62**	0.36
Parental household income (log)	0.96	0.10	0.57*	0.18	0.63***	0.08
N	3,250					
Pseudo R2	0.099					
BIC	4388.2					

Coefficients represent relative risk ratios; * p <0.1 ** p <0.05 *** p <0.01. Source: Statistics Netherlands, own calculations.

Table B.5.5: Multinomial logistic regression for moderations of automation risk (F&O) and social class: Parental homeownership

	Further Education		MBO		NEET	
	b	SE	b	SE	b	SE
Automation risk (F&O), ref. cat. Low						
High	1.20	0.17	1.66	0.64	1.48	0.63
Housing ownership, ref. cat. Owned						
Rented	1.06	0.12	1.35	0.43	1.69**	0.44
Interaction						
High X Rented	0.88	0.15	0.48	0.23	0.94	0.39
Parental education, ref. cat. Low						
Secondary	1.12	0.15	1.41	0.45	0.80	0.16
Tertiary	1.82***	0.26	1.46	0.43	1.02	0.28
Personality and Cognitive Skills						
Cognitive skills	1.09	0.06	0.94	0.15	1.28**	0.15
Emotional stability	1.07	0.05	1.28	0.25	0.82*	0.10
Extraversion	0.85***	0.04	0.75*	0.12	0.79**	0.08
Conscientiousness	0.93	0.05	0.86	0.13	1.08	0.12
Agreeableness	1.01	0.06	0.90	0.14	0.93	0.13
Autonomy	1.21***	0.06	1.08	0.15	0.91	0.09
Occupational linkage	0.98*	0.01	1.01	0.01	1.03*	0.02
Services	2.14***	0.38	0.35**	0.14	1.18	0.40
Gender, ref.cat.: Male						
Female	0.65***	0.10	1.42	0.50	3.01***	0.94
Immigration backgr., ref.cat. No						
Migrant	1.82***	0.28	1.35	0.64	1.98***	0.45
Level, ref. cat.: MBO3						
MBO4	3.85***	0.95	0.68	0.22	0.93	0.28
Parental household income (log)	0.95	0.10	0.58*	0.17	0.63***	0.08
N	3,250					
Pseudo R2	0.098					
BIC	4395.6					

Coefficients represent relative risk ratios; * p <0.1 ** p <0.05 *** p <0.01. Source: Statistics Netherlands, own calculations.

Table B.5.6: Multinomial logistic regression for moderations of automation risk (S&F) and social class: Parental homeownership

	Further Education		MBO		NEET	
	b	SE	b	SE	b	SE
Automation risk (S&F), ref. cat. Low						
High	1.11	0.13	1.21	0.41	1.82	0.68
Housing ownership, ref. cat. Owned						
Rented	1.01	0.09	1.42	0.37	1.74***	0.31
Interaction						
High X Rented	0.97	0.15	0.38*	0.20	0.89	0.34
Parental education, ref. cat. Low						
Secondary	1.12	0.16	1.45	0.46	0.79	0.16
Tertiary	1.81***	0.27	1.48	0.44	1.00	0.28
Personality and Cognitive Skills						
Cognitive skills	1.09	0.06	0.95	0.15	1.26**	0.15
Emotional stability	1.07	0.06	1.27	0.24	0.81*	0.10
Extraversion	0.86***	0.04	0.74*	0.12	0.79**	0.09
Conscientiousness	0.93	0.05	0.85	0.13	1.08	0.13
Agreeableness	1.01	0.06	0.90	0.14	0.93	0.13
Autonomy	1.21***	0.06	1.06	0.15	0.91	0.09
Occupational linkage	0.97**	0.01	1.01	0.01	1.03**	0.01
Services	2.05***	0.32	0.31***	0.12	1.10	0.34
Gender, ref.cat.: Male						
Female	0.66***	0.10	1.34	0.50	3.41***	1.03
Immigration backgr., ref.cat. No						
Migrant	1.82***	0.27	1.44	0.67	1.94***	0.45
Level, ref. cat.: MBO3						
MBO4	3.73***	0.92	0.64	0.20	0.90	0.26
Parental household income (log)	0.95	0.10	0.58*	0.17	0.63***	0.08
N	3,250					
Pseudo R2	0.098					
BIC	4393.1					

Coefficients represent relative risk ratios; * p <0.1 ** p <0.05 *** p <0.01. Source: Statistics Netherlands, own calculations.

Table B.5.7: Multinomial logistic regression for moderations of automation risk (F&O) and social class: Parental household income

	Further Education		MBO		NEET	
	b	SE	b	SE	b	SE
Automation risk (F&O), ref. cat. Low						
High	1.16	0.18	1.45	0.49	1.42	0.43
Parental household income (log)	0.99	0.11	0.41***	0.11	0.67**	0.12
Interaction						
High X Parental household income (log)	0.91	0.14	2.24**	0.82	0.87	0.24
Parental education, ref. cat. Low						
Secondary	1.12	0.16	1.44	0.46	0.80	0.16
Tertiary	1.83***	0.27	1.41	0.41	1.01	0.29
Personality and Cognitive Skills						
Cognitive skills	1.09	0.06	0.95	0.15	1.28**	0.15
Emotional stability	1.07	0.05	1.28	0.25	0.82*	0.10
Extraversion	0.85***	0.04	0.75*	0.12	0.78**	0.08
Conscientiousness	0.93	0.05	0.86	0.14	1.08	0.12
Agreeableness	1.01	0.06	0.91	0.14	0.93	0.13
Autonomy	1.21***	0.06	1.07	0.15	0.91	0.09
Occupational linkage	0.98*	0.01	1.01	0.01	1.03*	0.02
Services	2.13***	0.38	0.35**	0.14	1.18	0.40
Gender, ref.cat.: Male						
Female	0.66***	0.10	1.43	0.51	2.99***	0.94
Immigration backgr., ref.cat. No						
Migrant	1.80***	0.28	1.40	0.65	1.98***	0.45
Level, ref. cat.: MBO3						
MBO4	3.84***	0.95	0.68	0.22	0.93	0.28
Rented	0.99	0.10	0.89	0.26	1.65**	0.37
N	3250					
Pseudo R2	0.098					
BIC	4394.1					

Coefficients represent relative risk ratios; * p <0.1 ** p <0.05 *** p <0.01. Source: Statistics Netherlands, own calculations.

Table B.5.8: Multinomial logistic regression for moderations of automation risk (S&F) and social class: Parental household income

	Further Education		MBO		NEET	
	b	SE	b	SE	b	SE
Automation risk (S&F), ref. cat. Low						
High	1.10	0.13	0.96	0.30	1.76**	0.49
Parental household income (log)	0.95	0.11	0.41***	0.10	0.59***	0.12
Interaction						
High X Parental household income (log)	1.00	0.16	2.89**	1.22	1.11	0.31
Parental education, ref. cat. Low						
Secondary	1.12	0.16	1.45	0.47	0.79	0.16
Tertiary	1.82***	0.27	1.41	0.42	1.01	0.29
Personality and Cognitive Skills						
Cognitive skills	1.09	0.06	0.96	0.15	1.26**	0.15
Emotional stability	1.07	0.06	1.27	0.25	0.81*	0.10
Extraversion	0.86***	0.04	0.74*	0.12	0.79**	0.09
Conscientiousness	0.93	0.05	0.87	0.13	1.08	0.13
Agreeableness	1.01	0.06	0.90	0.13	0.93	0.13
Autonomy	1.21***	0.06	1.07	0.15	0.91	0.09
Occupational linkage	0.97**	0.01	1.01	0.01	1.03**	0.01
Services	2.05***	0.32	0.30***	0.11	1.09	0.34
Female	0.66***	0.10	1.39	0.52	3.42***	1.05
Immigration backgr., ref.cat. No						
Migrant	1.82***	0.28	1.49	0.68	1.94***	0.45
Level, ref. cat.: MBO3						
MBO4	3.73***	0.92	0.63	0.20	0.90	0.26
Rented	0.99	0.10	0.91	0.26	1.64**	0.37
N	3,250					
Pseudo R2	0.098					
BIC	4391.5					

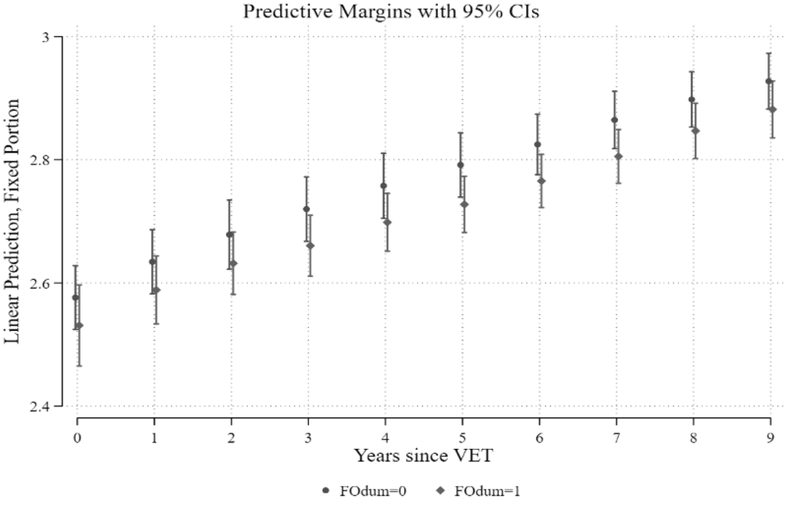
Coefficients represent relative risk ratios; * p <0.1 ** p <0.05 *** p <0.01. Source: Statistics Netherlands, own calculations.

B.6 Additional tables and figures: Wage regression

Table B.6.1: Random-effects growth curve models of log hourly wages

	Model GC0		Model GC1	
	b	SE	b	SE
Intercept	2.729***	0.003	2.567***	0.003
Years since VET			0.038***	0.000
Variance components				
Between	0.036***	0.001	0.047***	0.001
Within	0.035***	0.000	0.013***	0.000
Random slope (Years)			0.001***	0.000
Covariance intercept-slope			−0.003***	0.000
N (Person-years)	48,892		48,892	
N (Persons)	5,471		5,471	
ICC	0.506		0.781	
BIC	-12,927.81		-45,192.31	

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Statistics Netherlands, own calculations.



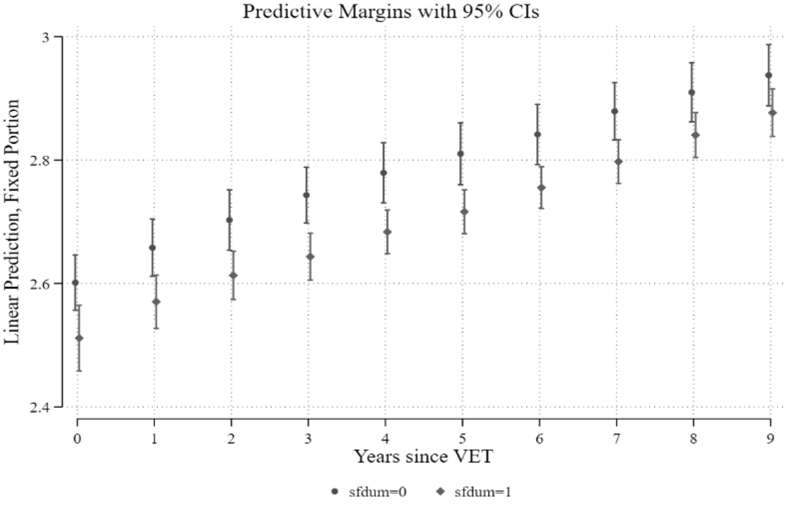


Figure B.6.1: Time trends of wage growth with yearly dummies.
Source: Statistics Netherlands, own calculations.

Table B.6.2: Random-effects growth curve models of wages on automation risk (F&O)

	Base		Linkage		clustered SE		w/o small level-fields	
DV: Real log hourly wage	b	SE	b	SE	b	SE	b	SE
Intercept	2.596***	0.004	2.554***	0.010	2.554***	0.052	2.555***	0.052
Years since VET	0.038***	0.000	0.038***	0.000	0.038***	0.002	0.038***	0.002
Automation risk (F&O), ref. cat. Low								
High	−0.060***	0.005	−0.046***	0.006	−0.046	0.036	−0.046	0.036
Occupational linkage			0.002***	0.000	0.002	0.002	0.002	0.002
Variance components								
Between	0.046***	0.001	0.046***	0.001	0.046***	0.004	0.046***	0.004
Within	0.013***	0.000	0.013***	0.000	0.013***	0.001	0.013***	0.001
Random slope (Years)	0.001***	0.000	0.001***	0.000	0.001***	0.000	0.001***	0.000
Covariance intercept-slope	−0.529***	0.016	−0.522***	0.016	−0.522***	0.047	−0.521***	0.047
ICC	0.778		0.776		0.776		0.776	
BIC	-45,311.7		-45,322.2		-45,322.2		-45,349.0	
N (Person-years)	48,892		48,892		48,892		48,783	
N (Persons)	5,471		5,471		5,471		5,458	

* p <0.1 ** p <0.05 *** p <0.01; Source: Statistics Netherlands, own calculations.

Table B.6.3: Random-effects growth curve models of wages on automation risk (S&F)

	Base		Linkage		clustered SE		w/o small level-fields	
DV: Real log hourly wage	b	SE	b	SE	b	SE	b	SE
Intercept	2.617***	0.004	2.583***	0.008	2.583***	0.038	2.583***	0.038
Years since VET	0.038***	0.000	0.038***	0.000	0.038***	0.002	0.038***	0.002
Automation risk (S&F), ref. cat. Low								
High	−0.096***	0.005	−0.088***	0.005	−0.088**	0.029	−0.089**	0.029
Occupational linkage			0.002***	0.000	0.002	0.002	0.002	0.002
Variance components								
Between	0.045***	0.001	0.044***	0.001	0.044***	0.004	0.044***	0.004
Within	0.013***	0.000	0.013***	0.000	0.013***	0.001	0.013***	0.001
Random slope (Years)	0.013***	0.000	0.013***	0.000	0.013***	0.001	0.013***	0.001
Covariance intercept-slope	−0.528***	0.016	−0.523***	0.016	−0.523***	0.046	−0.522***	0.047
BIC	-45,517.7		-45,528.4		-45,528.4		-45,558.2	
ICC	0.771		0.769		0.769		0.769	
N (Person-years)	48,892		48,892		48,892		48,783	
N (Persons)	5,471		5,471		5,471		5,458	

* p <0.1 ** p <0.05 *** p <0.01; Source: Statistics Netherlands, own calculations.

C Appendix to Chapter 5

C.1 Full model

Table C.1.1: Discrete-time event history analysis of available support by grandparents, log odds form logistic regression of entry into and exit out of NEET.

Dependent Variable:	Enter NEET		Exit NEET	
	b	SE	b	SE
Partner				
Household situation, ref. cat.: single				
Cohabitating	−0.049*	0.019	0.154**	0.019
Married	−0.078**	0.023	0.111**	0.023
Partner's activity before birth, ref. cat.: Education†				
Working	−0.294**	0.047	0.217**	0.048
NEET	0.058	0.042	−0.161**	0.040
Part-time Work	0.003	0.075	0.122	0.076
Partner's immigration backgr., ref.cat.: Both parents NL-born†				
Caribbean	0.023	0.067	0.108	0.069
Moroccan	0.126*	0.054	−0.273**	0.054
Surinam	0.185**	0.050	−0.028	0.051
Turkish	0.143**	0.055	−0.063	0.056
Western	0.072	0.037	0.055	0.038
Non-Western	0.020	0.054	0.087	0.052
Wage as percentage of partner's wage, ref.cat.: no income from either†				
no income from YM	0.087	0.052	−0.052	0.053
up to 33%	0.050	0.088	−0.485**	0.101
33% to 66%	−0.398**	0.080	−0.262**	0.093
66% to 100%	−0.852**	0.082	−0.059	0.095
100% and more	−0.986**	0.094	−0.109	0.108
no income from Partner	−0.390**	0.064	−0.239**	0.079
Grandparents				
Matched grandparents				
Grandmother matched	−0.065	0.041	0.126**	0.039
Grandfather matched	−0.099**	0.024	0.104**	0.024
Father's mother matched	−0.106**	0.028	0.143**	0.028
Father's father matched	−0.058*	0.023	0.090**	0.023

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Table C.1.1 – continued from previous page

	Enter NEET		Exit NEET	
	b	SE	b	SE
Number of grandparents within 3km, ref. cat.: no‡				
1	0.024	0.020	0.072**	0.020
2	−0.105**	0.017	0.152**	0.018
3	−0.169**	0.027	0.144**	0.027
4	−0.275**	0.026	0.213**	0.027
Monthly activity maternal grandmother, ref. cat.: Part-time work‡				
Full-time	0.027	0.018	0.032	0.019
Unemployment/Welfare benefits	0.191**	0.023	−0.176**	0.024
Sickness/Other benefits	0.159**	0.025	−0.206**	0.026
Pension	0.023	0.049	−0.096	0.050
other	0.108**	0.021	−0.129**	0.023
Monthly activity maternal grandfather, ref. cat.: Full-time work‡				
Unemployment/Welfare benefits	0.158**	0.025	−0.171**	0.026
Sickness/Other benefits	0.131**	0.023	−0.172**	0.024
Pension	0.025	0.035	−0.081*	0.035
other	0.125**	0.039	−0.121**	0.040
Monthly activity paternal grandmother, ref. cat.: Part-time work‡				
Full-time	0.020	0.021	−0.000	0.022
Unemployment/Welfare benefits	0.175**	0.028	−0.179**	0.029
Sickness/Other benefits	0.105**	0.029	−0.057	0.030
Pension	0.108**	0.034	−0.046	0.035
other	0.035	0.024	−0.096**	0.025
Monthly activity paternal grandfather, ref. cat.: Full-time work‡				
Unemployment/Welfare benefits	0.137**	0.029	−0.163**	0.031
Sickness/Other benefits	0.105**	0.025	−0.121**	0.026
Pension	0.046	0.026	−0.061*	0.027
other	0.016	0.048	−0.055	0.053
Individual variables				
Activity before birth, ref. cat.: VET				
Higher Education	−0.338**	0.030	0.408**	0.032
NEET	1.365**	0.029	−1.319**	0.033
Secondary Education and below	−0.048	0.035	−0.279**	0.039
Working	0.174**	0.063	0.389**	0.079
Part-time Work	0.664**	0.067	0.314**	0.081
Children, ref. cat.: no				
1	−0.180**	0.040	−0.421**	0.100

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Table C.1.1 – continued from previous page

	Enter NEET		Exit NEET	
	b	SE	b	SE
2	-0.232^{**}	0.047	-0.407^{**}	0.102
3+	-0.073	0.076	-0.719^{**}	0.110
Immigration backgr., ref.cat. Both parents NL-born				
Caribbean	-0.054	0.051	0.151^{**}	0.049
Moroccan	0.339^{**}	0.046	-0.194^{**}	0.048
Surinam	-0.005	0.036	0.139^{**}	0.034
Turkish	0.353^{**}	0.050	-0.060	0.051
Western	0.075^{*}	0.033	0.028	0.033
Non-Western	0.004	0.044	0.109^{*}	0.043
Urbanization, ref. cat.: rural				
Urban	0.061^{**}	0.017	-0.073^{**}	0.018
Very urban	0.116^{**}	0.023	-0.119^{**}	0.023
Province, ref. cat.: Drenthe				
Flevoland	-0.063	0.054	0.090	0.052
Friesland	-0.011	0.050	0.066	0.049
Gelderland	-0.144^{**}	0.045	-0.011	0.044
Groningen	-0.086	0.052	-0.078	0.052
Limburg	-0.016	0.049	-0.015	0.049
Noord-Brabant	-0.087	0.045	0.067	0.044
Noord-Holland	-0.247^{**}	0.046	0.182^{**}	0.044
Overijssel	-0.060	0.048	-0.004	0.047
Utrecht	-0.182^{**}	0.049	0.096^{*}	0.048
Zeeland	-0.176^{**}	0.057	0.115^{*}	0.057
Zuid-Holland	-0.245^{**}	0.045	0.124^{**}	0.043
Time relative to first childbirth, ref. cat.: -24 months to -13 months				
-12 to -6 months	0.827^{**}	0.022	-0.760^{**}	0.032
-5 to 0 months	2.141^{**}	0.022	-2.817^{**}	0.051
+1 to +6 months	1.432^{**}	0.048	-0.534^{**}	0.104
+7 to +24 months	1.108^{**}	0.046	-0.660^{**}	0.104
+25 to +60 months	1.205^{**}	0.050	-0.586^{**}	0.105
Age (centered)	-0.074^{**}	0.005	0.015^{**}	0.005
Age squared	-0.013^{**}	0.001	-0.004^{**}	0.001
Length of current spell	-0.027^{**}	0.001	-0.044^{**}	0.001
Constant	-4.154^{**}	0.066	-1.746^{**}	0.065
Individual-level random effect	0.491^{**}	0.015	0.337^{**}	0.017

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Table C.1.1 – continued from previous page

	Enter NEET		Exit NEET	
	b	SE	b	SE
Events	35,528		33,264	
Persons	30,905		24,040	
Person-months	1,891,586		824,942	
ICC	0.130		0.093	
-2LL	-161,288.047		-121,471.407	

* $p < 0.05$, ** $p < 0.01$

† These variables are coded zero for single mothers.

‡ These variables are coded zero in case of no matched grandparent.

Source: Statistics Netherlands, own calculations.

C.2 Interaction model

Table C.2.1: Discrete-time event history analysis of formal childcare availability interacted with availability of informal childcare, logistic regression of entry into and exit out of NEET.

	Enter NEET		Exit NEET	
	b	SE	b	SE
Number of childcare facilities within 3km, ref. cat.: No				
1-3	-0.161^{*}	0.063	0.086	0.067
3+	-0.218^{**}	0.061	0.100	0.064
Number of grandparents within 3km, ref. cat.: No				
1	-0.031	0.113	0.035	0.129
2	-0.341^{**}	0.079	0.301^{**}	0.085
3	-0.279	0.170	0.499^{**}	0.149
4	-0.690^{**}	0.125	0.453^{**}	0.142
Interaction terms				
1-3 X 1	0.101	0.120	0.011	0.137
1-3 X 2	0.120	0.086	-0.094	0.093
1-3 X 3	0.059	0.179	-0.311	0.161
1-3 X 4	0.329^{*}	0.132	-0.244	0.150
3+ X 1	0.058	0.115	0.029	0.131
3+ X 2	0.293^{**}	0.082	-0.180^{*}	0.087
3+ X 3	0.162	0.173	-0.373^{*}	0.152
3+ X 4	0.489^{**}	0.128	-0.258	0.145
Constant	-3.925^{**}	0.088	-1.878^{**}	0.090
Individual-level random effect	0.494^{**}	0.016	0.330^{**}	0.017
Events	33,180		31,292	
Persons	30,658		23,858	
Person-months	1,772,469		786,175	
ICC	0.131		0.091	
-2LL	-150,892.804		-114,901.492	

* $p < 0.05$, ** $p < 0.01$

Variables not shown: Time to birth (piecewise constant), Number of children, Mother's prior economic activity, Immigration background, Age, Age-squared, Length of current spell, Urbanization grade, Province, Partners prior activity, Partner's immigration background, Relative wage, Grandparental activity.

Source: Statistics Netherlands, own calculations.

C.3 Literature overview

Table C.3.1: Literature overview of grandparental childcare and mothers' labor market activities

Author	Year	Countries	Data type	Age of mothers	Years studied	Sample size (mothers)	Methods	Dependent variable
Del Boca	2002	IT	panel	36	1991-1995	1708	FE panel regression; ITT (grandparent alive)	Working at time of interview
Dimova & Wolff	2008	FR	cross-sectional survey	33	2002-2003	2202	Probit family RE & FE effects logit & 2SLS with endogenous grandchildcare	LFP at time of interview

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Table C.3.1 – continued from previous page

Author	**Year**	**Countries**	**Data type**	**Age of mothers**	**Years studied**	**Sample size (mothers)**	**Methods**	**Dependent variable**
Dimova & Wolff	2011	AT, CHE, DE, DK, ES, FR, GR, IT, NL, SWE	cross-national panel (cross-sectional)	36	2004	2317	Probit and family-FE	LFP at time of interview
Aassve, Arpino & Goisis	2012	BG, DE, FR, GEO, HU, NL, RU	cross-sectional survey	20-55	2004	ca. 1000 per county	Probit IV (maternal grandmother alive & number of siblings of mother)	LFP at time of interview
Posadas & Vidal-Fernandez	2013	US	panel	18-49	1979-2006	14659	FE & IV (grandmother's death)	LFP

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Table C.3.1 – continued from previous page

Author	Year	Countries	Data type	Age of mothers	Years studied	Sample size (mothers)	Methods	Dependent variable
Compton & Pollak	2014	US	cross-sectional survey & census data	25-60 & 18-45 (military wives)	2000 (military wives)	ca. 2500 (married women), 1637 (unmarried women), 10578 (military wives)	Probit/Tobit IV (proximity)	Weekly working hours, LFP/employment
Aparicio Fenoll & Vidal-Fernandez	2014	IT	cross-sectional survey	20-40	1998-2009 (three waves)	3.612	TS2SLS IV (changes in retirement eligibility)	LFP at time of interview
Arpino et al.	2014	IT	cross-sectional survey	37	2003	3852	2SLS IV (1-4 grandparents alive)	LFP at time of interview

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Table C.3.1 – continued from previous page

Author	Year	Countries	Data type	Age of mothers	Years studied	Sample size (mothers)	Methods	Dependent variable
Compton	2015	CAN	cross-sectional survey	45-60	2007	ca. 3000	Probit(Work), Tobit(Work hours)	Work/Work hours
Bratti, Frattini & Scervini	2018	IT	rotating panel	20-49	1993-2006	8402	LPM; ITT: retirement eligibility	LFP in a given year
Zamarro	2020	AT, BE, DE, DK, ES, FR, GR, IT, NL, SWE	cross-national panel (cross-sectional)	34	2004	1452	Probit IV (retirement eligibility)	LFP at time of interview

Continued on next page

Table C.3.1 – continued from previous page

Author	Year	Countries	Data type	Age of mothers	Years studied	Sample size (mothers)	Methods	Dependent variable
Aparicio Fenoll	2020	AT, BE, CHE, CZ, DE, DK, ES, FR, GR, IRL, IT, LUX, NL, PL, PT, SLO, SWE	cross-national panel	23-50	2004-2015	25,794	2SLS IV (changes in retirement eligibility); ITT	LFP at time of interview

C.4 Coefficient plots

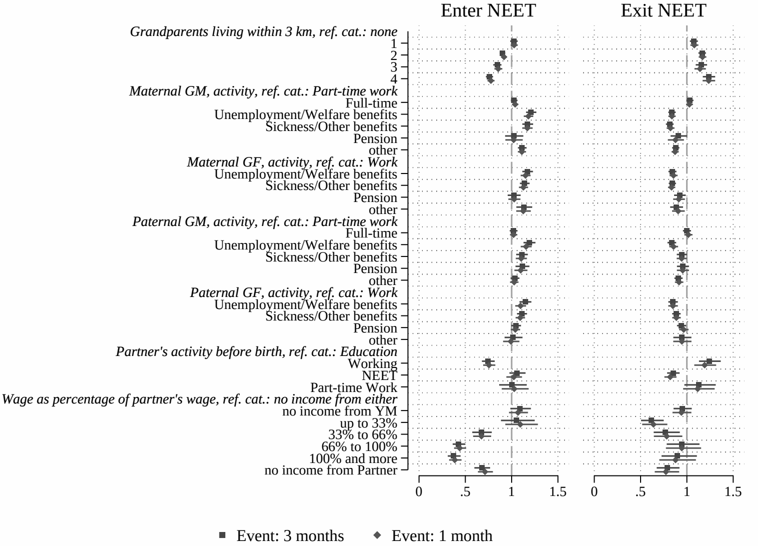

Figure C.4.1: Coefficients from discrete-time event-history analysis of main variables of interest, logistic regression of entry into and exit out of NEET with two different operationalizations of event duration. Source: Statistics Netherlands, own calculations

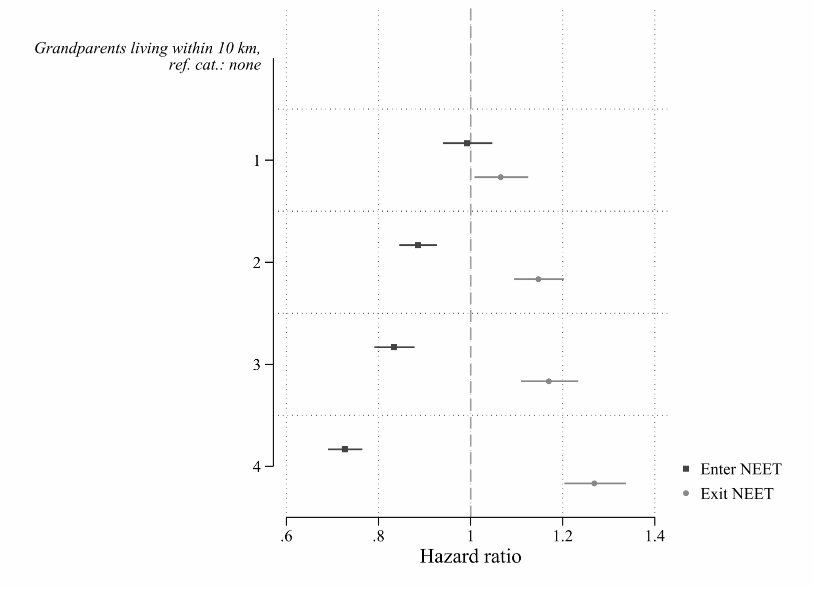

Figure C.4.2: Coefficients of grandparental availability within 10 km, discrete-time event-history analysis (hazard ratios) of entering and exiting NEET. Source: Statistics Netherlands, own calculations

D Appendix to the Impact Paragraph

An evidence-based intervention program aimed at prevention and reintegration of NEETs in Limburg

As described in **Chapter 1**, the Netherlands is the country in the EU with the lowest number of young people who experience NEET. However, within the Netherlands, the province of Limburg has relatively high NEET rates. Moreover, contrary to the national trend, the number of young people who become NEET are rising in Limburg. Earlier research carried out by the ROA as part of the 4Limburg-program shows that youth with the greatest distance to the labor market are overwhelmingly found in the former eastern mining district in the east of Limburg (ROA, 2018, 2020).

In the 4Limburg program, we developed experimental interventions that could succeed in preventing young people from experiencing NEET, or become reintegrated back into to work. A good evaluation should be conducted in such a way that we are able to make hard statements about the effectiveness of the interventions. For this purpose, experimental research is needed. However, little such research exists, and the application of existing evaluation studies to the specific situation in Limburg is limited. As a result, there is no clarity on how to get youth who are NEET back to work or in education in Limburg.

To this end, we, collaborated with representatives of various civil society organizations and knowledge institutions in Limburg (including Zuyd University of Applied Sciences and Youth GGZ Maastricht) to design two interventions that combine features of several successful interventions. One of these interventions will be described in the following sections[2].

Intervention

The number of programs that have been rolled out in the Netherlands as part of the Youth Employment Approach is very diverse, but what a large proportion of the apparently effective interventions seem to have in common is:

1. A very personal approach of a social worker, who cares about the young person, does not judge but listens, finds out what is holding

[2] Based on Levels, M. (2020). *Een evidence-based interventieprogramma gericht op preventie en reintegratie van NEETs in Limburg.* ROA Technical Reports Nr. 007 https://doi.org/10.26481/umarot.2020007

them back, and helps to remove barriers (see for example 'Werkend Leren' and other approaches summarized in Regioplan, 2017).
2. A clear, achievable, predetermined objective. In this case: finding a suitable job or further training, and holding on to that job or further training for at least six months.
3. Little government involvement: The social worker is not (or at least not visibly) from the government. Preliminary discussions we held with youth workers revealed that the government is seen as an opponent by many of these young people.
4. Good cooperation with stakeholders who may want or be able to hire young people. In this case, schools, and employers.

Individually, these factors appear to contribute strongly to the success of other youth-focused interventions in Limburg and across the country and are all strongly embedded in both the practical and scientific literature on successful reintegration pathways. In dialogue with youth workers and representatives of various relevant NGOs, we identified these elements as critical success factors. By combining these elements into a single, unified intervention, the proposed methodology aims to substantially reduce the number of youths who are long-term NEET in the former eastern mining district. We named this approach "NEET in Parkstad". Specifically, our proposed intervention has the following features:

- Invitations to social organizations active in Limburg to apply the "NEET in Parkstad" method in their approach.
- Voluntary participation: Young people themselves sign up for the intervention.
- Participation in the "NEET in Parkstad" program is a maximum of 8 weeks, during which a social worker (who explicitly should not be a government official) tries to find out through personal conversations what motivates the participant and what life goals he or she has. The practical obstacles that the participant experiences in achieving these life goals are also identified. In an intensive counseling program, these barriers are addressed by the young person and counselor.
- The program is aimed at successful reintegration, either into the labor market or into education.
- A successful intervention means that a young person who was previously NEET finds a job or starts training or education and continues to do so for at least six months. To this end, the social workers make use of a network of employers and educational institutions.

Given the success of such programs, both in the Netherlands and abroad, the risk of failure in Limburg is very small. But the fact that something works in one place does not mean that it will work in another. Moreover, we want to strive to optimize the effectiveness of the interventions: that something works does not mean that the maximum effect has been achieved with this approach. We therefore propose to organize a smart cycle of evidence-based policy interventions that will ensure that we maximize the effectiveness of our intervention. To this end, we propose that the scientists and researchers of Maastricht University and Zuyd University of Applied Sciences accompany the implementation process with a thorough evaluation study. Through a field experiment and additional qualitative research, the researchers will be able to firmly establish the causal impact of our intervention on the reintegration of young people. The quantitative research aims to determine which intervention works and in which places and under which circumstances the intervention works best; the qualitative research uncovers why.

To organize this, the proposed intervention must be conducted as a field experiment. This means that participants must be divided into two groups. Of all participants, 50% follow a regular program ("control group") and 50% follow the "NEET in Parkstad" program ("intervention group"). Allocation shall be random so that any differences in outcomes can be attributed solely to the intervention. Of all young people, it will then be recorded after 8 weeks whether they have found a job or started training. Of the youth for whom this applies, it should then be recorded after 6 months whether they still have this job.

Implementation

Specifically, the implementation of intervention involves ten consecutive phases, which aim to maximize the efficiency of the intervention and measure its effectiveness. These phases are:

1. Finding participants
2. Administering registrations
3. Qualitative research
4. Pre-measurement (survey of a number of characteristics)
5. Assignment of participant to caseworkers
6. Treatment
7. Post-measurement
8. Registry study
9. Impact evaluation

10. Policy change

One of the main challenges in researching youth with a distance to the labor market and education is finding and contacting them as they are almost by definition difficult to reach through usual channels (work or school). Not infrequently, they disappear from the radar, even with social organizations. We therefore propose a three-track contacting policy:

- Through the existing network of municipalities and social organizations: The *Vereniging Kleine Kernen Limburg*, for example, has a good overview of young people in problematic situations in small towns; caseworkers in the municipalities of Heerlen, Kerkrade and Landgraaf also know which young people are most vulnerable.
- Through social media: Many young people are active on and can be reached via social media. The Zuyd University of Applied Sciences (lectureship HRM) has started a preliminary study into the possibilities of reaching these young people via social media, which we find promising.
- Through concrete recruitment actions in the living environments of youths. One of Limburg's most successful reintegration actions was done by Lieve Schouterden, who helped a large group of long-term unemployed to reintegrate. She successfully recruited (older) long-term unemployed by advertising in their neighborhoods. A similar approach could be followed here as well. In neighborhoods, young people can be reached through direct recruitment actions (flyers, leaflets, bus shelters).

Young people must be able to apply for the program throughout the recruitment period. The administration of the registrations takes place centrally, preferably at a social organization so that the threshold is low. For this purpose, an accessible channel for young people must be set up, preferably via social media or an instant messaging service. If necessary, social workers of municipalities can help young people to register. After registration, the intervention should start immediately.

To make the interventions in Limburg as effective as possible in the long term, it is necessary to find out why the program works better for some young people than for others. Hence, qualitative research is necessary. To get a good picture of possible explanations for the effectiveness, at least 30 in-depth interviews will have to take place.

Pre-measurement (survey into a number of characteristics)

A pre-measurement should take place. This should entail the socioeconomic status of the youth, as well as their distance to education and the labor market. In addition, a questionnaire shall be administered to all young people who register. In this questionnaire several background characteristics are asked for, and a first inventory of possible challenges is made. This questionnaire is also important for the success of the field experiment on effectiveness, because the information helps to determine whether the intervention group and the control group resemble each other on important characteristics.

Assigning youths to caseworkers

In the next phase, participants should be paired with caseworkers. That pairing should be randomized, with 50% of all youth assigned to the treatment group, and 50% to the control group. Only the caseworkers in the treatment group will follow the "NEET in Parkstad" methodology.

Treatment

The treatment consists of the following:

- A social worker (who explicitly does not act as a government official) finds out what motivates the participant and what his or her life goals are.
- Through a structured interview, practical barriers that the participant experiences in achieving these life goals are identified.
- In dialogue with the participant, the caseworker draws up a personal and tailor-made counselling trajectory, which should last eight weeks.
- In the counselling trajectory, these thresholds are addressed by the young person and the counsellor together, and then lowered or removed.

Post-measurement

After the end of the intervention, it is to be recorded whether the participant has found a job or started an education or training. After six months, it should be again recorded if the young person is still in that job or training.

Register comparison

An additional sample could be drawn from the register data of the CBS and matched on cohort characteristics. This group can act an additional control group, which will allow to further investigate the role of self-selection (participants have to apply themselves) and contacting strategies (participants have to be reached) for the effectiveness of the interventions to be understood and measured.

Social proceedings

This experiment can generate the following concrete outputs:

- Social reintegration of a large part of the participating youth.
- A test of the effectiveness of the program.
- A report of the findings of the qualitative research, including key insights about the motivations of youth who are long-term NEET.
- Policy recommendations for municipalities and provinces based on the evaluation study, and upon request, presentations of the insights obtained at the participating and other Limburg municipalities.
- A manual with practical tips for youth care providers in the rest of the province and in the country, based on the insights generated by the program, containing a concrete roadmap for the implementation of the program in other regions.

Preparation and conditions

In order to roll out “NEET in Parkstad”, a number of preparatory steps are necessary. At the very least, the following:

- Commitment from civil society organizations, both at the operational level (the caseworkers) and on an administrative level.
- Train caseworkers in the “NEET in Parkstad” method. To this end, five workshops can be facilitated by researchers (e.g., from Maastricht University) and led by experienced social workers.
- Finding companies and schools via the networks of civil society organizations, which are willing to contribute to the reintegration of youths, by offering a job or a training place.
- Produce recruitment materials.
- Create a social-media portal where participants can sign up. Possibly by or in collaboration with students from Zuyd University of Applied Sciences, Fontys, or Maastricht University.

Curriculum Vitae

Alexander Dicks (1989) received his Bachelor of Science in Social Sciences from the University of Cologne in Germany in 2014 and his Master of Science in Sociology and Social Research from Utrecht University in 2016. He then joined the Research Centre for Education and the Labour Market (ROA) as a PhD candidate in 2016. During his PhD, Alexander was a junior visiting scholar at Nuffield College at the University of Oxford and has presented his research at several international conferences, including ISA RC28, European Consortium for Sociological Research (ECSR), Transitions in Youth (TIY), and the Society for Longitudinal and Lifecourse Studies (SLLS). In 2019, he co-organized the 27th annual workshop Transitions in Youth (TIY) in Maastricht.

Alexander currently works for the WZB Berlin Social Science Center where he serves as the coordinator of *Stage 6: Vocational Training and Transition to the Labour Market* of the German National Educational Panel Study (NEPS). He is currently involved in the operative planning and content development of future studies by developing items to measure digitalization at the work place or occupational aspirations of young people.

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