Non-standard Employment: Prospect or Precarity?

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Non-standard Employment: Prospect or Precarity?

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Authors' contributions

Chapter 1: Written by Lucille Mattijssen. Several rounds of feedback were provided by supervisors Dimitris Pavlopoulos, Wendy Smits and Harry Ganzeboom.

Chapter 2: Written by Lucille Mattijssen. The research idea was conceived by Lucille Mattijssen and Dimitris Pavlopoulos. Lucille Mattijssen conducted the statistical analyses and drafted the chapter. Dimitris Pavlopoulos critically revised the chapter. Several rounds of feedback were provided by supervisors Harry Ganzeboom and Wendy Smits.

Chapter 3: Written by Lucille Mattijssen. The research idea was conceived by all authors Lucille Mattijssen conducted the statistical analysis. Wendy Smits contributed to the construction of the Linkage scale. Lucille Mattijssen drafted the chapter. Dimitris Pavlopoulos and Wendy Smits critically revised the chapter. Harry Ganzeboom provided several rounds of feedback to the chapter.

Chapter 4: Written by Lucille Mattijssen. The research idea was conceived by all authors. Lucille Mattijssen conducted the statistical analyses and drafted the chapter. Dimitris Pavlopoulos and Wendy Smits critically revised the chapter. Harry Ganzeboom provided several rounds of feedback to the chapter.

Chapter 5: Written by Lucille Mattijssen. The research idea was achieved by all authors. Lucille Mattijssen conducted the statistical analyses and drafted the chapter. Dimitris Pavlopoulos and Wendy Smits critically revised the chapter. Harry Ganzeboom provided several rounds of feedback to the chapter.

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Technical Appendix II: Written by Lucille Mattijssen. Lucille Mattijssen conducted the statistical analyses.

1

Synthesis

Lucille Mattijssen

1.1. Introduction

In the last decades, non-standard employment – employment with contract types that deviate from the 'standard' permanent contract, such as fixed-term contracts, on-call contracts and temporary work agency contracts – has become an increasingly more standard form of employment in industrialized labour markets. Many countries have experienced significant increases in the share of non-standard employment, though some countries more than others (Eurostat, 2021d).

As non-standard employment became more common in labour markets, the share of research focusing on non-standard employment increased accordingly. Many studies have investigated both the causes as well as the consequences of the growth of non-standard employment. Non-standard employment creates advantages for employers by offering them flexibility in adapting their workforce. For workers, general consensus exists that it is an inferior form of employment compared to standard, permanent employment: on average, workers in non-standard employment earn lower wages, have fewer promotion possibilities, have lower levels of job security and receive less fringe benefits and training (Booth, Francesconi, & Frank, 2002; De Beer, 2016). The increase in the share of non-standard employment in the labour market is seen as a cause of increasing social inequalities and the main factor consolidating the divide between the primary and secondary segments of the labour market (Gash & McGinnity, 2007; Kalleberg, 2001; Scherer, 2004).

As non-standard employment is found to be, ceteris paribus, inferior to permanent employment, a central question in quite some studies has been: does non-standard employment offer prospects of more secure, permanent employment, or does it trap workers in the precarity of repeated spells of low-paid non-standard employment, potentially interchanged with periods of unemployment? Even though this question has been asked repeatedly, the answer remains inconclusive: some find that non-standard employment offers workers prospects of permanent employment (Booth et al., 2002; McGinnity, Mertens, & Gundert, 2005), while others find that non-standard employment results in the precarity of repeated, low-paid non-standard employment or unemployment (D'Addio & Rosholm, 2005; Giesecke & Groß, 2003). Even within the same institutional contexts, multiple studies result in contradicting outcomes (De Lange, Gesthuizen, & Wolbers, 2013; Mooi-Reci & Dekker, 2015).

In this dissertation, I advance on previous research by using a multidimensional processual approach to answer the question to what extent non-standard employment offers prospects or results in precarity. With this approach, the quality of outcomes can be based on evaluations of the employment security and income security that are experienced in continuous career paths, rather than on snapshots in time of separate outcomes. By using this approach, I can redefine ‘prospects’ and ‘precarity’ as career outcomes, moving beyond the traditional definition of a successful career according to whether the worker manages to get a permanent job or not. Furthermore, this approach not only allows for the existence of other outcomes than the traditional approach allows, but also for all these outcomes to exist simultaneously. This means that non-standard employment can result in a range of career outcomes that vary in quality. This more nuanced image of career outcomes of non-standard employment creates new opportunities to not investigate *whether* non-standard employment results in either prospects *or* precarity, but rather *to what extent* non-standard employment results in prospects *and* precarity.

By allowing a range of career outcomes of non-standard employment to exist concurrently, I can also give more nuanced insights in the factors that influence whether non-standard employment offers prospects or results in precarity. In this dissertation, I will particularly look into three main determinants of the outcomes of non-standard employment coming from economic, sociological and human resource management perspectives: educational qualifications, occupational characteristics, and employer strategies. Especially the latter two determinants, that focus more on the demand side of the labour market, have not received a lot of attention from previous research. This dissertation aims to fill these gaps in the literature.

In this synthesis, I will first discuss the broader literature on the outcomes of non-standard employment, how a multidimensional processual approach allows for better investigating the role of non-standard employment in the career, and the economic, sociological and human resource management perspectives on which factors influence the outcomes of non-standard employment. These perspectives will take the centre stage in the chapters of this dissertation. I will also describe the institutional context of the Netherlands, in which the empirical chapters of this dissertation are embedded. Second, I briefly introduce the data and the method I use for my multidimensional processual approach: multichannel sequence analysis. Third, I provide an overview of the empirical chapters and the main findings. Fourth and finally, I synthesize the results from this dissertation and reflect on the conclusions that can be drawn from the empirical chapters, as well as the challenges and limitations of this dissertation.

1.2. Theoretical framework

1.2.1. Defining non-standard employment

Though a formal definition of non-standard employment does not exist, it is usually defined as all employment that deviates from 'standard' employment: employment with a permanent contract with fixed working hours. This means that the concept of non-standard captures a very broad range of employment types that all offer employers some type of flexibility. This flexibility can be functional, allowing employers to employ workers for various types of jobs within the firm, or numerical, allowing employers opportunities to adapt the number of workers in the firm (Atkinson, 1984). In this dissertation, I focus on types of non-standard employment that offer employers numerical flexibility.

Within numerical flexibility, a distinction can be made between external numerical flexibility and internal numerical flexibility. External numerical flexibility offers employers options to adapt the number of workers at the firm by turning to the external labour market. Examples of types of employment that offer external numerical flexibility are fixed-term contracts, temporary work agency employment, and the use of solo self-employed workers. Internal numerical flexibility in contrast gives employers options to adapt how many and how many hours their employees are working in their firm, without turning to the external labour market. Examples of types of employment that offer internal numerical flexibility are on-call employment or part-time employment (De Beer, Dekker, & Olsthoorn, 2011).

In this dissertation, I investigate the career outcomes of the most common types of non-standard dependent employment in the Netherlands. These are fixed-term employment and temporary work agency employment, that are forms of external numerical flexibility, as well as on-call employment, which is a form of internal numerical flexibility. Seen from the broad perspective of labour market flexibility, on-call employment and temporary work agency employment create insecurity for the worker that extends beyond the duration of the employment contract. Specifically, on-call employment is associated with insecurity in working hours and therefore also in income, while temporary work agency employment is related to both employment and income insecurity, but additionally insecurity in the workplace where temporary agency workers are employed. Therefore, although in some cases on-call jobs and temporary work agency jobs may be permanent, the negative aspects that are related to these contracts persist.

There are two types employment that offer employers numerical flexibility that are specifically not central in this dissertation. The first one is part-time employment, which I fully exclude from my definition of non-standard employment. The main reason for excluding part-time employment from the definition is that in the country of interest in this dissertation, the Netherlands, part-time employment can hardly be considered as non-standard. 46.8% of the working population, and 73.4% of women, worked part-time in 2019, compared to EU-27 averages of 17.8% and 29.4% respectively (Eurostat, 2021c). Moreover, as part-time work is fully integrated in the social and labour law regulations, working part-time does not have negative consequences for the career of the individual in terms of employment security. A large share of the individuals working part-time do so voluntarily, for instance to combine work and care tasks (Portegijs & Keuzenkamp, 2008). Adapting working hours to preferences of the employee is also secured in Dutch employment legislation (Hevenstone, 2010). As a consequence, the Netherlands have one of the lowest shares of involuntary part-time employment in Europe: in 2019, only 13.7% of part-time working employees indicated that they would prefer to work more hours (CBS Statline, 2021b). In contrast, 60% of workers with a fixed-term contract have a fixed-term contract out of necessity: they could not find a permanent job or are new in their firm (Hooftman et al., 2019).

The second form of non-standard employment that is not central in this dissertation is solo self-employment.[1] This is a data-driven choice and, considering the high popularity of this form of employment in the Netherlands, it is a limitation of this thesis. Though I do consider solo self-employment to be a type of non-standard employment (Kalleberg, 2000), the individuals working as solo self-employed are very diverse. As stated before, working on a fixed-term contract is often not preferred by the workers. In contrast, for quite a large group of solo self-employed, self-employment is a voluntary choice, for instance made because they prefer to work outside an employee relationship or to have more autonomy in their work (Van der Torre et al., 2019). A small but significant group of solo self-employed workers however are forced to work as solo self-employed by employers who want to circumvent all employment protection regulation regarding paid employment. Though formally being solo self-employed, they are still dependent on one particular employer (Kösters & Smits, 2017). This latter group would be very interesting to take into account in this dissertation as well, but unfortunately, it is often, and also in this dissertation, not possible to distinguish these 'dependent self-employed' from the overall group of solo self-employed workers methodologically in register data. Next to this, self-employment is only registered on a yearly basis, making it complicated to determine the exact start and end dates of self-employment. In this dissertation, I will therefore focus on the careers of workers who start working in fixed-term contracts, on-call contracts and temporary work agency contracts, but not on workers who start

1 Other terms for solo self-employment include own-account workers and portfolio workers (in Dutch: *Zelfstandigen Zonder Personeel, ZZP'ers*).

working in self-employment. However, if these workers at some point throughout the observation window earn their main income from self-employment, self-employment (without distinguishing between different types of it) is included as a labour market position in the analyses.

1.2.2. Non-standard employment: prospect or precarity?

Theory presents two opposing scenarios for the career outcomes of non-standard employment for workers. On the one hand, the *stepping stone* scenario argues that non-standard employment offers workers prospects of permanent employment. This scenario is based on human capital theory (Mincer, 1974), which argues that workers acquire skills and experience when working on non-standard contracts. These skills and experience subsequently would improve their career prospects, both in terms of contract type and income. Signalling theory (Spence, 1973) furthermore supports the stepping stone scenario: it suggests that employers possess imperfect information on the productivity of new hires and use temporary jobs as a screening device during the probation period. If the worker meets the employer's expectations, the employer offers the worker a permanent contract.

On the other hand, according to the *trap* scenario, non-standard employment most likely results in precarity for workers. Based on dual labour market theory (Doeringer & Piore, 1971), this scenario argues that non-standard employment contracts are mainly used by employers to adapt their workforce to economic fluctuations. As seen before, non-standard employment contracts offer employers the numerical flexibility to easily hire workers in an economic upturn, but also to lay them off when economic conditions deteriorate (Kalleberg, 2000). This means that non-standard jobs do not offer any job security for workers, as their employers have no reason to offer them a permanent contract. Next to this, employers have little to no incentives to invest in the human capital of their workers on non-standard contracts, as these workers are only hired for a limited period. As a consequence, non-standard employment does not only have negative outcomes on the short term, with a lack of job security at their current firm, but also on the long term (Berton, Devicienti, & Pacelli, 2011). An employment history that includes several spells of non-standard employment might function as a signal of lower productivity for future employers. Future employers might first of all assume lower productivity as they are aware that these workers likely have not received much training in their previous non-standard jobs. Furthermore, employers could attribute the non-conversion of the previous non-standard contract fully to the personal failure of the worker, rather than to their previous employer not having any motive to offer permanent contracts. As a result, these future employers might be less likely to hire workers with a history of non-standard employment, or offer them another non-standard contract instead. Non-standard employment may thus have a scarring effect on the career prospects of workers (Mooi-Reci & Dekker, 2015). Both the stepping stone scenario as well as the trap scenario are also known under a variety of other names (see Box 1.1).

Box 1.1: Naming outcomes of non-standard employment

In the literature, there has been a large variety of names given to the two main outcomes of non-standard employment. Here, I provide a (possibly non-exhaustive overview) of these names.

Table B1: Names for outcomes of non-standard employment

Outcome	Name	Research
Prospect	Stepping stone/Step	Addison et al., 2015; Babos, 2014; Baranowska et al., 2011; Booth et al., 2002; de Graaf-Zijl et al., 2011; Esteban-Pretel et al., 2011; Givord & Wilner, 2015; Hopp et al., 2016; Pavlopoulos, 2013; Scherer, 2004
	Bridge	Fuller & Stecy-Hildebrandt, 2015; Gash, 2008; Leschke, 2009; McGinnity et al., 2005; Reichelt, 2015; Steijn et al., 2006; Wolbers, 2010
	Port/Path of Entry	Berton et al., 2011; D'Addio & Rosholm, 2005
	Chance	Giesecke & Groß, 2003
	Blessing	Mooi-Reçi & Dekker, 2015
	Springboard	Ichino et al., 2008; Picchio, 2008
	Winner	Remery et al., 2002
Precarity	Trap	Berton et al., 2011; Gash, 2008; Ichino et al., 2008; McGinnity et al., 2005; Reichelt, 2015; Scherer, 2004; Steijn et al., 2006; Wolbers, 2010
	Dead end	Addison et al., 2015; Booth et al., 2002; D'Addio & Rosholm, 2005; Esteban-Pretel et al., 2011; Faccini, 2014; Pavlopoulos, 2013; Picchio, 2008
	Risk	Giesecke & Groß, 2003
	Scar	Mooi-Reçi & Dekker, 2015
	Loser	Remery et al., 2002
	Vicious cycles	Hopp et al., 2016
	Impediment	Helbling, 2017

Up until now, research has often tried to answer the question which of both scenarios holds. However, the answers to this question remain mixed. Some find that non-standard employment mostly offers prospects, while others find that it mostly results in precarity. Though a part of the variation can be explained by variation in contexts of study, mixed results are also found within single contexts. For the Netherlands, for instance, de Lange et al. (2013), de Graaf-Zijl et al. (2011) and Steijn et al. (2006) conclude that non-standard employment offers prospects, while Mooi-Reçi and Dekker (2015) and Wolbers (2010) conclude the contrary and find that non-standard employment results in precarity.

1.2.3. Defining prospects and precarity

What most previous studies on the outcomes of non-standard employment have in common is that they lack a holistic view in evaluating the quality of outcomes. In previous studies, the definition of prospects and precarity is often limited in at least one of the following three ways:

First, the quality of the outcomes of non-standard employment is determined based on outcomes at fixed points in time (e.g.: employment position or income *t* months or years after starting in non-standard employment, McGinnity et al., 2005), or on the duration until a particular outcome (usually permanent employment) is achieved (D'Addio & Rosholm, 2005; Gash, 2008). Though both these approaches provide useful first insights, they also have in common that they cannot take into account relevant events that occur both before and after the outcome of interest. The events that occur before the outcome of interest, however, might have an impact on the likelihood of experiencing the outcome of interest. For instance, if one focuses on the probability of having a permanent contract one year later, it is relevant to take into account whether workers have been in employment steadily throughout that year, or whether workers experienced unemployment spells in between. These periods of unemployment are missed in the analysis, but actually might have further harmed the probability of having a permanent contract (Hopp, Minten, & Toporova, 2016; Pavlopoulos, 2013). Not taking into account events that happen after the outcome of interest is also not ideal, as it implies that the outcome of interest – i.e. a permanent contract – is an absorbing state. Though permanent contracts are named as such for a reason, they can be terminated, both voluntarily if workers find better employment elsewhere, as well as involuntarily, for instance when the firm goes bankrupt. Similarly, if one is unemployed at the time point of interest, this could either be a sign of long-term involuntary unemployment, but just as well a signal of short (voluntary) friction unemployment that is quickly succeeded by a new (and maybe even better) contract. By covering a longer period of time, the actual stability of employment can be better assessed. To my knowledge, the study by Fuller and Stecy-Hildebrandt (2015) was the first to apply a processual approach that addressed this issue with regards to studying non-standard employment.

Second, the quality of the outcome is based on one or separate dimensions of job quality, usually the labour market position (permanent contracts) or the income of workers. However, by focusing on these outcomes separately, the variance within these groups in terms of the other outcomes is missed. One for instance finds that incomes are on average lower for workers in non-standard employment, but misses that within this group of workers, there is large variation in income levels, due to trade-offs that workers might make between employment and income security. Therefore, to get a good grasp of the overall job quality, at least both aspects should be taken into account simultaneously (Tilly & Tilly, 1998).

Third, as an outcome of the previous limitation, the definition of a positive outcome is limited to one particular outcome, often permanent employment. Workers who remain in non-standard employment are then automatically labelled as unsuccessful. This limited definition neglects the fact that not all workers in non-standard employment are equally precarious: some non-standard jobs may have wages that are sufficiently high to compensate for the insecurity that accompanies non-standard employment. At the same time, the opposite also holds for permanent contracts: they might offer job security, but are for some not accompanied by a decent living wage (Thiede et al., 2015). Their reduced income security then detracts from their higher employment security. By focusing on permanent employment as the only good outcome, these nuances are missed.

At the same time, many studies have also not paid, or have not been able to pay, sufficient attention to the variation in types of non-standard employment (Givord & Wilner, 2015). Many studies merge all different types of non-standard employment together into one group (D'Addio & Rosholm, 2005; de Graaf-Zijl et al., 2011; Esteban-Pretel et al., 2011; McGinnity et al., 2005; Remery et al., 2002; Steijn et al., 2006). Others only focus on one specific type of non-standard employment, typically fixed-term contracts (Autor & Houseman, 2010; Hopp et al., 2016; Ichino et al., 2008; Pavlopoulos, 2013), while in some cases the type of non-standard employment that is studied is not clearly defined (Babos, 2014; Faccini, 2014; Giesecke & Groß, 2003; Picchio, 2008; Wolbers, 2010). If any variation in the types of non-standard employment is allowed, this is mostly limited to the distinction between fixed-term contracts and seasonal/casual work, which are then studied separately (Addison et al., 2015; Booth et al., 2002; de Lange et al., 2013; Leschke, 2009; McVicar et al., 2017). A notable exception is the study by Berton et al. (2011) in which the interplay of the effects of five types of temporary employment is studied. Distinguishing between different types of non-standard employment is however crucial when investigating their outcomes for workers (Berglund et al., 2017; Givord & Wilner, 2015; Kiersztyn, 2016). The types of non-standard employment namely vary considerably in their regulations and the security they offer workers. Furthermore, employers use various types of non-standard employment for different reasons (van Echtelt et al., 2015). For instance, employers often use fixed-term contracts as a probation period for their new workers, or because they are uncertain about future product demand. In contrast, temporary work agency workers and on-call workers are mostly used by employers to get more flexibility to adapt their workforce to short-term or frequent fluctuations in demand. On-call workers are also used to replace sick or absent workers. These various regulations and uses of non-standard employment thus mean that not all types of non-standard employment are equally precarious.

Though previous studies are useful to understand specific outcomes of non-standard employment, they are not suited when the aim is to understand the role of non-standard employment in the career. The result of the limited definitions of outcome quality has as a result that conclusions are drawn based on strong assumptions that do no justice to the dynamics of modern labour markets in which permanent employment is not necessarily a good nor final outcome and non-standard employment is diverse and not always precarious.

In this dissertation, I take a different approach that applies a broader and more holistic view in defining which types of careers offer prospects and which result in precarity. The key in doing so is the application of a multidimensional processual approach. I treat careers as continuous processes that are inherently dynamic. In my analyses, I take everything that happens during the career trajectory into account: the starting position, what types of (non-standard) employment and non-employment workers experience in their careers, as well as the number, order and duration of (non-)employment spells. Next to this, I define the career processes by two central dimensions of job quality simultaneously: employment positions and income. These two dimensions are part in defining the processes in the analysis, but also in the evaluation of the career outcomes of non-standard employment as successful or unsuccessful, as I can now evaluate the quality of careers based on the employment security and income security they provide.

By using a multidimensional processual approach, I provide a clear, more detailed, more informed, but also more complicated picture on which careers offer prospects and which careers result in precarity. This way, I can give a better image of labour market segmentation that the simple distinction between those who get permanent contracts and those who do not. The approach furthermore results in more valid explanations on the role of other factors – coming from economic, sociological and human resource management perspectives – that have been put forward as crucial in determining the outcomes of non-standard employment, as the outcomes I identify also do more justice to the dynamics of the labour market and the interplay between employment and income security.

1.2.4. Three perspectives on determinants of non-standard employment outcomes

The multidimensional processual approach for investigating the outcomes of non-standard employment offers new opportunities to investigate both older as well as newer questions regarding which factors influence the outcomes of non-standard employment.

In this dissertation, I chose to focus on new factors coming from three well-established perspectives: the economic perspective, the sociological perspective and the human resource management perspective. All perspectives provide explanations about when non-standard employment might offer prospects or result in precarity, but (parts of) these perspectives have remained under exposed in research so far.

The economic perspective, and in particular human capital theory, argues that educational qualifications are a major determinant of the outcomes of non-standard employment. Education namely provides a significant part of the human capital with which workers enter the labour market. If workers invest in increasing their human capital, they expect that their investments will be rewarded in terms of higher incomes or better employment prospects (Becker, 1993). While research has mostly focused on the effect of the level of education on the outcomes of non-standard employment, more and more attention is being paid to the effects of horizontal stratification on employment outcomes: differences between fields of study (Ballarino & Bratti, 2009; Giesecke & Schindler, 2008). The main factor explaining differences in employment outcomes between fields of studies is the specificity of the field of study. Three mechanisms explain how specificity might affect employment outcomes. First of all, graduates from specific fields of study would be more productive in occupations for which their specific skills are required (Becker, 1993). Second, graduates from specific fields of study more often have access to credentialized occupations (Collins, 1979). Third and finally, fields of study also provide signals to employers about trainability (Thurow, 1975). Though it could be argued that graduates from general fields of study signal higher trainability because they have a more broad range of skills, it could also be argued that specific fields of study signal higher trainability because these are often perceived as more difficult than general fields of study (Barone & Schindler, 2014; Iannelli & Raffe, 2007). Though the effect of specificity is strongly dependent on the context, it has been found to be an advantage in the Dutch labour market, resulting in better employment outcomes (Bol & Van de Werfhorst, 2011). Does this however also hold when using a processual approach for investigating employment outcomes? Furthermore, is specificity an asset for each level of education and for more cyclically sensitive fields of study as well?

The sociological perspective identifies occupations as a crucial factor in social stratification (Parsons, 1949). Occupations largely determine which type of employment employers use for the jobs they offer (Goldthorpe, 2007). For some occupations, using non-standard employment is more beneficial for employers than for other occupations. One important factor determining whether non-standard employment is beneficial for employers is whether the worker can be easily replaced. The replaceability of workers is dependent on the skill level, skill specificity and the extent to which workers can be monitored in the occupation. The easier, more general and easily monitorable an occupation is, the more replaceable a worker is: there are many people who can execute that occupation, and the fact that their performance can be monitored is sufficient motivation for the worker to be productive. In these cases, employers do not need to offer permanent contracts to retain workers with the right skills or to motivate workers to remain productive (Lepak & Snell, 1999). As a result, it would also mean that non-standard employment is more likely to offer prospects in high and specific skilled, not-easily monitorable occupations, and to result in precarity for workers in low and general skilled, easily monitorable occupations. While the skill level of occupations can be measured with relative ease, the skill specificity and monitorability are in itself more difficult to measure. However, both aspects come together in the concept of routine: routine tasks can easily be expressed in rules and regulations, which makes them both easy to monitor as well as easy to execute without requiring specific skills (Kiersztyn, 2016; Reichelt, 2015). This raises the question: can the skill level and task composition of occupations explain when non-standard employment is a prospect or results in precarity?

The human resource management perspective stresses the importance of managerial agency in decisions concerning the use of non-standard employment. Employers' strategies for using non-standard employment are central mechanisms in the two scenarios for the outcomes of non-standard employment. Employers can use non-standard employment to screen workers, to be able to adapt their workforce, or to reduce costs (Abraham & Taylor, 1996; Atkinson, 1984; Spence, 1973). The way in which employers use non-standard employment strongly determines the outcomes of non-standard employment for workers in that firm: if the employer has no intent whatsoever to give a worker a permanent contract, non-standard employment is not only quite unlikely to become a prospect at that firm, but the employers is also less likely to invest in the human capital of these workers, that might have scarring effects for the rest of these workers' career trajectories be (Mooi-Reci & Dekker, 2015). However, it is difficult to derive how employer use non-standard employment: stated motives for using non-standard employment might not align with how employers' use non-standard employment in practice, and some employers might not have a thought-trough strategy or motive for using non-standard employment at all (Hakim, 1990). They use non-standard employment ad hoc in response to quickly changing situations (Stanworth & Druker, 2006), or even just because their competitors do so too (De Beer, 2018). However, if strategies are defined as 'patterns in a stream of decisions' rather than as predetermined plans (Mintzberg, 1978), there are several firm-level non-standard employment practices – i.e. how much non-standard employment they use, how many non-standard contracts are converted to permanent contracts, how much excess mobility there is in the firm – that reveal firms' non-standard employment strategies. Can these non-standard employment practices predict whether non-standard employment in firms works offers prospects or results in precarity?

1.2.5. Non-standard employment in the Netherlands: Institutional context

This dissertation uses data from the Netherlands. The Netherlands are generally considered to be a coordinated market economy with a strongly coordinated labour market (Hall & Soskice, 2001). There is a lot of strategic interaction between employers' organisations and labour unions to make agreements on labour conditions, both at a central as well as a sectoral level. Though unionization levels are relatively low, collective labour agreements can be declared generally binding, covering all employees in all firms in the sector. As a result, relatively many workers are covered by collective labour agreements without being union members themselves (De Beer & Verhulp, 2017).

Though it is mostly data availability that drove the decision to focus on the Netherlands, the Netherlands are also an interesting case from the perspective of non-standard employment. Compared to other European countries, the Netherlands have experienced a very large increase in the share of non-standard employment in the last two decades. Compared to the European average of 2019, the Netherlands has relatively many fixed-term contracts (20.2% vs. 13.6%[2]), solo self-employed (15% vs. 9.6%) and temporary work agency workers (3.8% vs. 2%) (Eurostat, 2021d, 2021e, 2021a). The share of on-call workers has furthermore almost doubled in the last 15 years (CBS Statline, 2021c).

The main drivers of the developments in non-standard employment are legislative changes that were made in the last part of the 20th century. The first steps towards a liberalisation and flexibilization of the labour market were made in the 1982 Wassenaar agreement (Touwen, 2008). Following a period with high levels of unemployment in the 1970's, employers and employee organisations came to an agreement to moderate wages in exchange for reduced working hours and early retirement. Furthermore, part-time and short-term employment were stimulated. As a result, unemployment rates decreased significantly. Another agreement in 1993 resulted in more flexibilization of working times and a further reduction of working hours (Stichting van de Arbeid, 1993).

Though these changes made the Dutch labour market already more liberal and flexible, the employment protection for workers with permanent contract remained quite

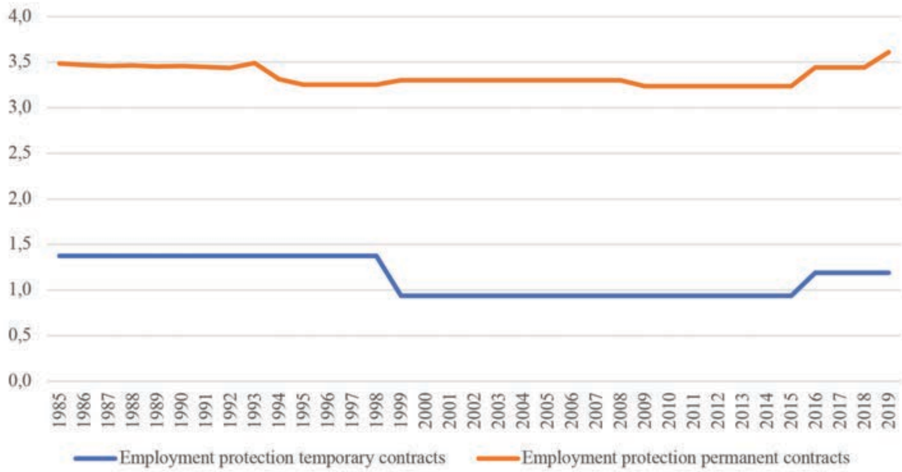
2 These percentages include temporary work agency workers and on-call workers. There are no internationally comparable numbers available on the share of fixed-term contracts excluding temporary work agency workers and on-call workers. In the Netherlands in 2019, the share of fixed-term contracts excluding on-call workers and temporary work agency workers is 12.8% (CBS Statline, 2021c).

strict: employers could only dismiss permanent workers with approval of the public employment office or via legal procedures. Next to this, severance pay packages had become very common too, making dismissal an even more costly affair. At the same time, the use of fixed-term contracts was restricted: fixed-term contracts were considered to be permanent if they were continued beyond 31 days (De Beer & Verhulp, 2017). As a consequence of these restrictions, the share of temporary work agency workers increased significantly during the 1990's (Kremer, Went, & Knottnerus, 2017). This type of employment was, in contrast to permanent and fixed-term employment, not strictly regulated (Knegt, Klein Hesselink, Houwing, & Brouwer, 2007).

To decrease the gap and to regulate the use of temporary work agency employment, the Law Flexibility and Security (in Dutch: *Wet Flexibiliteit en Zekerheid, WFZ*) was implemented in 1999. One of the biggest changes made by this law is that it increased the possibilities for employers to use fixed-term contracts (Heerma van Voss, 1998). With the WFZ, employers could now use up to three fixed-term contracts in succession for a period of three years in total. After three contracts or years, the fixed-term contract was automatically converted to a permanent contract. Next to this, temporary work agency employment was now formally classified as an employment relation, and provided with regulations concerning training, pension and employment security. For on-call workers, a rule was implemented that secured on-call workers of at least three hours pay for every time they would be called-in for work, even when they would in practices work less than three hours. For permanent contracts, the dismissal procedures were shortened. With these regulation, the government wanted to satisfy the wishes of employers to be able to have more flexibility in their workforce, while at the same time protecting employees from continuous employment insecurity and income insecurity caused by repeated fixed-term contracts (Heerma van Voss, 1998).

Following the implementation of this law, the share of fixed-term contracts increased significantly. In practice, the employment protection for permanent contracts only decreased slightly, and the increase of the employment protection of temporary work agency workers was practically outweighed by the decrease of employment protection for fixed-term contracts. Next to this, in 2004 the total duration of sick pay – to be paid by the employer – increased from one to two years. This increased the risk of hiring workers on permanent contracts, as for workers with fixed-term, the obligation for sick pay ended at the end of the employment contract, usually less than two years away (Kremer et al., 2017). Combined, these developments did not lead to a convergence in the protection of fixed-term and permanent contracts, but rather to a further increase in the gap, making fixed-term contracts more attractive for employers. This is also visible in the scores of the Netherlands on the Employment Protection Legislation Index (OECD, 2020), which is determined by several employment protection characteristics, resulting in a scale varying from 0.5 for the lowest levels of employment protection and 6 for the highest levels of employment protection. Figure 1.1 shows first of all the large difference in employment protection between fixed-term contracts and permanent contracts in the Netherlands. Next to this, the overall employment protection for fixed-term contracts decreased after 1999 with the introduction of the WFZ.

Figure 1.1: Employment protection index for the Netherlands, 1985-2019



Source: OECD (2020).

The WFZ remained in place until 2015, and thus covers practically all workers analysed in this dissertation. The main regulations are presented in Table 1.1. In 2015, a new law that aimed to further decrease the gap between fixed-term and permanent employment was implemented, the Law Work and Security (in Dutch: *Wet Werk en Zekerheid, WWZ*). The main change introduced by this law was the reduction of the maximum duration of fixed-term contracts to two years, and the increase of the *cooling off* period between fixed-term contracts at the same employer from three to six months. However, as this dissertation focuses on cohorts starting in 2010 the latest, this new legislation is likely to not have been of very large influence on the careers of the workers in the analyses.

Table 1.1: Main employment regulations in place during the period analysed in this dissertation (WFZ, 2007-2015)

Maximum number of successive fixed-term contracts at the same employer	Max. 3 contracts within max. 3 years[1]
Minimum duration between fixed-term contracts at the same employer if the 3 year/contracts requirement is exceeded	3 months
Valid cases for using fixed-term contracts	All
Temporary work agency employment protection	Temporary agency employment is considered to be an employment agreement • Phase 1 (first 6 months): Limited protection: end of assignment is end of TWA contract. • Phase 2 (after 6 months): right of schooling and pension • Phase 3 (after 12 months): right of employment contract of at least 3 months with the temporary work agency • Phase 4 (after 18 months (same agency) or 36 months (different agencies)): right of a permanent contract with the temporary work agency
Valid cases for the use of temporary work agency employment	All, except seamen
On-call employment	Right of 3 hours wages per call (if contract <15 hours without fixed working times, or no fixed hours per week), even if there is less work
Dismissal permanent contracts	Via public employment office: long procedure Via court (*kantonrechter*): shorter, but more expensive
Severance pay in case of dismissal permanent workers	Via public employment office: no severance pay Via court: dependent on tenure
Probation period	2 months (1 month for contracts < 2 years)[1]
Sick pay	2 years (or until the end of the fixed-term contract)

[1] Deviation from this regulation possible in collective labour agreements

1.3. Research design and data

1.3.1. Data

The main data source used in this dissertation is the System of Social Statistical Datasets (SSD, in Dutch: *Stelsel van Sociaal-Statistische Bestanden)*, collected by Statistics Netherlands. This dataset contains micro level register data on employment, welfare and other characteristics for all individuals who are registered in the Netherlands. Statistics Netherlands collects this data by combining data from the basic integral registration (*Polisadministratie*), the Dutch tax administration (*Belastingdienst*) and the Dutch Employee Insurance Agency (‘*UWV’*) (Bakker, Van Rooijen, & Van Toor, 2014).

In chapters 2, 4 and 5, I use a particular subset of the SSD that focuses on all individuals aged between 15 and 74 who started working in dependent non-standard employment. Workers are included only if they did not work in non-standard employment in the three months before starting a new non-standard job. The included individuals can be tracked from the moment they enter non-standard employment. In chapters 2 and 4, I focus on the cohort of workers who start in non-standard employment in 2007, whose careers could be tracked for eight years (96 months). Chapter 5 focuses on the cohort of workers who enter non-standard employment in 2010, whose careers could be tracked for six years (72 months).

In chapter 3, I deviate from the default population of workers starting in non-standard employment, and use data from the SSD for the full population of school-leavers who leave education between October 1st 2009 and September 30th 2010, irrespective of their first type of employment contract. I chose this population as it provides advantages for investigating the effects of educational characteristics on employment outcomes. First, complete information on education for all levels of education is only available for the relatively younger cohorts of workers, as the Educational Archives have 'only' been available since the early 2000's. For older cohorts, there is only limited information on education available, from the samples of the Dutch Labour Force Survey (Linder, Van Roon, & Bakker, 2011). Next to this, as age and work experience increase, the influence of one's education on employment outcomes decreases. To fully capture the effects of education, it is thus better to focus on a cohort that has recently left education.

Though the SSD contains a lot of information, it does not contain all information that was required for the explanatory analyses in this dissertation. Therefore, I needed to link additional information to the register data in chapter 3 and 4. In chapter 3, I linked information from the Educational Archives to the SSD (Linder et al., 2011). The Educational Archives contain highly detailed information from various sources on the full education history of the cohort, including the national standardized codes assigned to each unique education program. For chapter 4, information about occupations of workers was not available for all workers, as occupation is not registered in the integral registers. Information about occupations was therefore retrieved from the Dutch Labour Force Survey for the four waves of 2007 and the first wave of 2008 (Statistics Netherlands, 2008). As the LFS is a survey, using data about occupations strongly reduced the number of cases that could be included in the analysis.

Though I believe that the register data from the SSB are the best data available in the Netherlands for studying non-standard employment with a processual approach, using register data is quite challenging. The data for instance are not perfect: any mistakes that are made during registration result in measurement error. Research has shown that the measurement error in the SSB has as a result that the transition rate from fixed-term to permanent employment is highly overestimated (Pankowska, Pavlopoulos, Bakker, & Oberski, 2020). Next to this, the data provide a tempting amount of detail, allowing to distinguish a large variety of labour market positions and to reconstruct career trajectories accurate to the day. Though a high level of detail is generally preferable, too much detail might overcomplicate further analyses. Luckily, it is up to researchers to decide which level of detail is used in the analyses. Finally, given that register data contain integral information about full populations, the datasets are delightfully huge. However, a downside to this is that data processing and analysis may take a lot of time, and that not all analyses might be able to run on the full dataset.

1.3.2. Multichannel sequence analysis

The central analytical method in this dissertation is (multichannel) sequence analysis. Sequence analysis is a statistical method that allows for describing a series of states that subsequently can be classified in terms of similarity (Cornwell, 2015). Specifically, it measures the similarity of the various sequences that are present in the data and classifies these sequences into clusters, based on their similarity. Sequence analysis has its origin in genetics for the purpose of studying DNA sequences or coronaviruses, but is increasingly being used in the social sciences for studying longitudinal phenomena. Like DNA-sequences, longitudinal phenomena can also be seen as a succession of states. The main difference is that social sequences of longitudinal phenomena have an aspect of time in them, while this is not the case for DNA. Many have now applied sequence analysis for studying life courses or career trajectories (e.g. Elzinga & Liefbroer, 2007; Scherer, 2001; Struffolino et al., 2015). Recently, researchers are also starting to apply (single-channel) sequence analysis to investigate the outcomes of non-standard employment (Fuller & Stecy-Hildebrandt, 2015; Ojala, Nätti, & Lipiäinen, 2017; Reichenberg & Berglund, 2019).

In contrast to other statistical methods used for life course research, such as event-history analysis, sequence analysis in itself does not aim to establish causality (Abbott & Tsay, 2000). Some may consider this a strong disadvantage (Levine, 2000; Wu, 2000). However, I concur with Abbott and Tsay (2000) who claim that description is a valuable but too often overlooked part of social science research. As sequence analysis shows, the various strings of events that occur give a more detailed picture of employment careers than more traditional methods such as transition tables, that only depict the situation on certain points in time, or Kaplan-Meier plots, that only show the cumulative occurrence of one specific event, such as the transition to permanent employment. Though the direct outcomes of sequence analysis in itself do not establish causality, typologies resulting from sequence analysis can be used in subsequent explanatory analyses.

A key concept in (multichannel) sequence analysis is the similarity of sequences. The similarity of sequences is used to cluster the sequences and to create sequence typologies, that subsequently can be used in explanatory analyses. The most widely used method to determine this similarity is Optimal Matching (Abbott and Forrest, 1986; Abbott and Tsay, 2000). To determine the similarity of sequences, this method takes into account the number of substitutions and permutations that are needed to make two sequences identical. The researcher can assign each change (i.e. substitution or permutation) a cost. Specifically, to make types of sequences more distant than others, one can decide to make certain changes more 'expensive' than others.

Though Optimal Matching is the most common method, it has a large number of variations, while there are also other methods that can be used to determine the similarity of sequences. For instance, Optimal Matching is rather insensitive to timing differences, as it allows for aligning sequences by inserting and deleting states (Studer & Ritschard, 2016). In the investigation of careers, this is an important disadvantage as timing is a very important aspect of careers: a career in which a transition to permanent employment occurs after three months differs considerably from a career in which that transition occurs after fifty months. This could have as a consequence that such careers are classified as similar, while they substantively differ from each other. To make the sequence analyses of this dissertation more sensitive to timing differences, I use a Hamming distance cost setting with constant substitution costs (Hamming, 1950). The Hamming distance prevents inserting and deleting states by assigning extremely high costs to such changes, which means that sequences can only be aligned by substituting states. This prevents important labour market transitions from being moved either forward or backward in time when determining the similarity of sequences. This way, the timing of events is prioritized (Studer & Ritschard, 2016).

In multichannel sequence analysis (Gauthier, Widmer, Bucher, & Notredame, 2010; Pollock, 2007), two or more channels per individual can be studied simultaneously. This extension of sequence analysis allows for implementing my multidimensional processual approach. In this dissertation, each individual will have one channel with a sequence of labour market positions and another channel with a sequence of incomes. These channels are linked: the labour market position of person 1 in time point 1 in the first channel occurs at the same time as the income of person 1 in time point 1 in the second channel. This multichannel nature complicates the determination of the similarity of sequences. Multichannel sequence similarity is determined following the approach of Pollock (2007). In this approach, the states of the two channels are first combined into a new sequence consisting of "multi-states". In this approach, the states of the two channels (A and B) are first combined into a new sequence consisting of "multi-states". In every time point the state of this new sequence is defined as the combination of the states of the two channels in the same time point (AB). Second, the similarity of the new sequences is determined. This is done by summing the substitution costs of the separate channels. For example, if the cost of moving from state A1 to state A2 is 1 and the cost of moving from state B1 to state B2 is 2 then, in the new sequence, the cost of replacing multi-state A1B1 for multi-state A2B2 is 3.

When the similarity of sequences is determined, the next step I take is to cluster the sequences based in a typology, based on this similarity. By creating a typology, I can distinguish what types of career trajectories workers who enter non-standard employment have. There are various algorithms via which data can be clustered, such as hierarchical clustering, partitioning around medoids or hybrid versions (Studer, 2013). To cluster sequences, I use the Ward clustering (Ward, 1963). The Ward clustering algorithm is an agglomerative hierarchical clustering method: it starts from all separate cases and starts grouping them step by step in such a way that as little information as possible is lost, until all cases are grouped into one cluster. I chose this clustering method because I did not have concrete expectations about what types of clusters would be in the typology and it is a quite common clustering method in previous research using sequence analysis (McVicar, Wooden, & Fok, 2017; Scherer, 2001).

To determine the optimal number of sequence clusters for the final typology, researchers can usually rely on cluster quality measures (Studer, 2013). In this dissertation, I could not use these measures due to the heterogeneity of the data. As many clusters still contained a lot of internal heterogeneity, most cluster quality measures would not even reach the minimum quality levels. This is a downside of using heterogeneous data that provide a lot of detail. Reducing the level of detail, for instance by shortening sequences or by reducing the possible number of states, this issue could be circumvented. However, I wanted to maintain as much details as possible to get the most nuanced image of career trajectories. In this, I made a clear choice of not wasting available information.

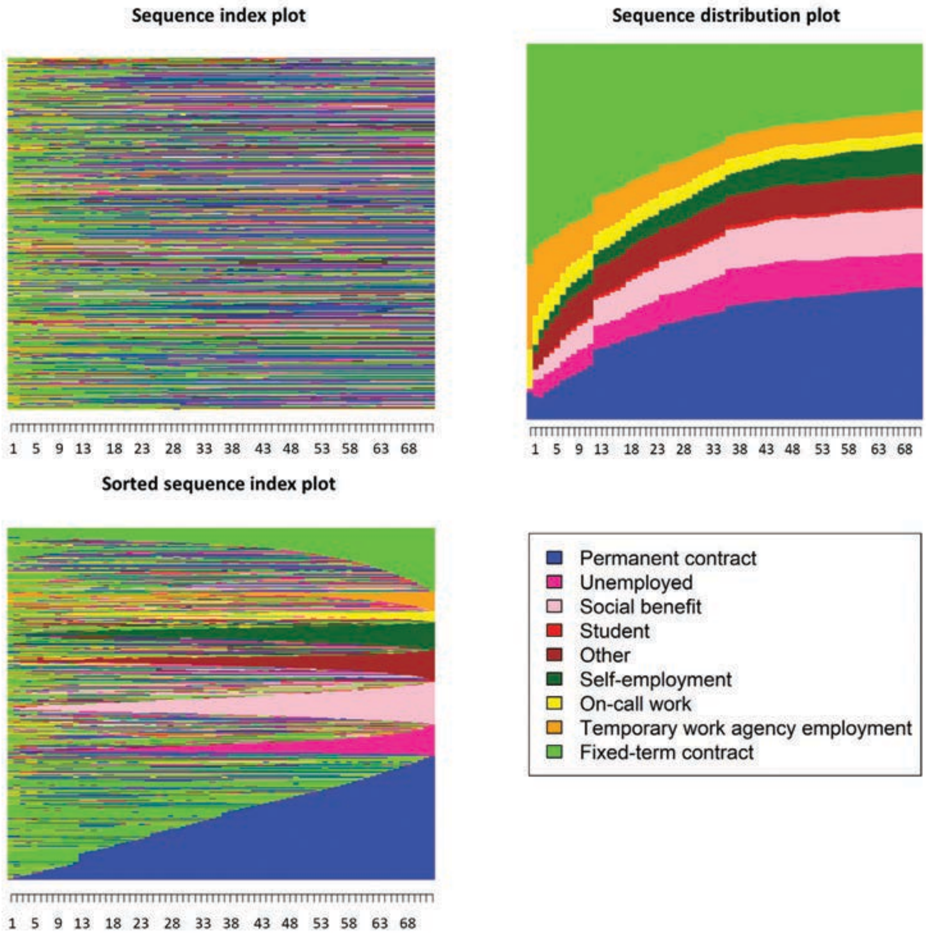
To create a robust typology despite the impossibility of using quantitative cluster quality measures, I developed a replication strategy. In this strategy, which is based on the bootstrap strategy developed by Hennig (2007), one runs several sequence analyses for different subsamples and qualitatively compares various cluster solutions per subsample. First, an optimal number of clusters k is determined. Subsequently, the k most reliable clusters are selected for the final typology. The complete procedure of the replication strategy is described in Technical Appendix I. This procedure is not only suited for creating a robust typology, but also allows for analysing datasets that are too large to be analysed at once with sequence analysis and assigning all sequences to the same typology. The replication strategy can furthermore be used when comparing different cohorts or subsets of the same population. This way, stability of typologies over time or across groups can be established. In Technical Appendix II, I illustrate this by comparing the typology for the 2007 cohort of workers who enter non-standard employment to the typology for the 2010 cohort of workers who enter non-standard employment.

The results of (multichannel) sequence analysis – usually typologies – are often presented using sequence index plots (Scherer, 2001). Index plots depict the sequences that are included in the analysis as horizontal bars, using different colours for each state. This way, one can see which types of trajectories are found in the analysis. However, as the sequences are by default presented in order of the data, it might seem like quite a mix, especially when clusters have quite some internal heterogeneity. Another option is then to present sequence distribution plots. These plots sort the states per position (time point) and give an overview of how the frequency of states develops over time. Though these plots are often more clear than index plots, they however no longer show the development of individual sequences over time. In this dissertation, I will present sorted index plots. In these plots, the sequences are sorted based on the last state of the sequence. This way, the development of individual sequences is still visible, while also creating a bit more order in the sequences.

For illustration, I have plotted the same set of sequences in an index plot, distribution plot and a sorted index plot in Figure 1.2. The index plot shows all individual sequences, but simply in order of appearance in the data. As a result, the image is quite vague and it is hard to tell, especially with a large number of sequences, what types of sequences are present in the data. The distribution plot in contrast is much clearer and shows the frequency of states across times points. However, the downside is that you cannot identify actual trajectories. For instance, a transition from fixed-term employment (light green) to permanent employment (dark blue) is a common trajectory, but those are not visible in this plot. The sorted index plot holds the middle ground between the index plot and the distribution plot, as it sorts the sequences based on the, in this case, last position. This way, we can identify the individual sequences and more easily observe what types of trajectories occur in the data, for these trajectories where individuals go from fixed-term contracts to permanent employment.

To run the sequence analyses for this dissertation, I have thankfully used the TraMineR package (Gabadinho, Ritschard, Mueller, & Studer, 2011) and the WeightedCluster package (Studer, 2013) in R (R Core Team, 2019) and the Graphviz software (Ellson, Gansner, Koutsofios, North, & Woodhull, 2004).

Figure 1.2: Various types of sequence plots



1.4. Overview of empirical chapters

This dissertation aims to describe the career outcomes of non-standard employment and to find determinants of these outcomes from economic, sociological and human resource management perspectives. This section summarizes the content and findings of the four empirical chapters of this dissertation. A schematic overview of the chapters can be found in Table 1.2.

Table 1.2: Overview of empirical chapters

	Chapter 2	Chapter 3	Chapter 4	Chapter 5
Research question	What are the career outcomes of non-standard employment?	What is the effect of educational specificity on the quality of school-to-work transitions?	How do the occupational skill level and task types affect the outcomes of non-standard employment?	How do employers' non-standard employment strategies affect the career outcomes of their workers with non-standard contracts?
Theoretical perspective	Prospect or precarity	Economic	Sociological	Human resource management
Research population	Workers in the Netherlands who start working in non-standard employment in 2007	School-leavers in the Netherlands from the 2009/2010 cohort	Workers in the Netherlands who start working in non-standard employment in 2007	Workers in the Netherlands who start working in non-standard employment in 2010
Data	SSB	SSB + educational archives	SSB + LFS	SSB + employer level aggregates of SSB
Methodology	Multichannel sequence analysis	Multichannel sequence analysis + multinomial logistic regression	Multichannel sequence analysis + multinomial logistic regression	Multichannel sequence analysis + multinomial logistic regression + dominance analysis
Main independent variable		Educational specificity Level of education Cyclical sensitivity	Occupational skill level Task types	Employers' non-standard employment practices
Main dependent variable	17 cluster typology of non-standard employment careers	14 cluster typology of school-to-work transitions	17 cluster typology of non-standard employment careers	17 cluster typology of non-standard employment careers
Main findings	30% of workers have a traditional prospects outcome, 40% of workers have a traditional precarious outcome, 25% have a career that is not easily classifiable as prospects or precarity due to trade-offs between employment and income security	Specificity results in school-to-work transitions with higher levels of employment and income security, mostly for MBO4 and HBO and for cyclically sensitive fields of study.	High skilled occupations do not protect against precarious careers. Routine tasks do not necessarily result in precarious careers, this only holds for routine-manual tasks.	Workers in firms with cost reduction strategies are most likely to have precarious careers. Working in firms with adaptability strategies does not have a scarring effect on the career compared to working in firms with screening strategies.

Chapter 2: A multichannel typology of non-standard employment careers in the Netherlands: Identifying traps and stepping stones in terms of employment and income security
In chapter two, I apply a multidimensional processual approach to create a typology of non-standard employment careers to answer the question to what extent non-standard employment offers prospects or results in precarity in the Dutch labour market. To create the typology of non-standard employment careers, I analyse the careers of workers who start working in non-standard employment in 2007 using multichannel sequence analysis. This way, all labour market positions and incomes they have in the eight years after entering non-standard employment can be taken into account.

The result from this analysis is a typology with 17 types of non-standard employment careers. These careers can be classified based on the employment security and income security they offer workers. The results show that almost 30% of the workers follows the prospects-scenario and has a career with both high levels of employment and income security. In contrast, almost 40% has a precarious career with low levels of both employment and income security, of which 16.6%-point does so while being employed. Next to this, almost 25% of the workers have a career that deviates from the traditional stepping stone or trap dichotomy based on employment status alone, as they have a career that combines high employment security with low income security, or a career that combines low employment security with high levels of income security.

This chapter shows that a more nuanced image of the outcomes of non-standard employment can be achieved by applying a multidimensional processual approach that allows for assessing the quality of outcomes based on the employment and income security experienced throughout the career trajectory.

Chapter 3: When does a specific field of study pay off? The interplay between educational specificity, level and cyclical sensitivity.
Non-standard employment plays a large role in the start of the career, during which recent graduates try to find a good match on the labour market. In chapter 3, I investigate how the specificity of the field of study influences the quality of the school-to-work transitions of school-leavers in the Netherlands of the 2009/2010-cohort. I furthermore assess two factors that might moderate the effect of specificity. First, the effect of specificity may vary per level of education, as not all levels of education have equally strong connections to employers. Second, the cyclical sensitivity could also moderate the effect of specificity. As the 2009/2010-cohort enters the labour market during an economic downturn, graduates from more cyclically sensitive fields of study might benefit less from specific fields of study as these make it more difficult for graduates to switch to other fields if employment demand in their own fields decreases.

Using a new typology of school-to-work transitions, created in the same way as the typology of chapter 2, I find that, in general, specificity positively affects the quality of school-to-work transitions. Graduates from more specific fields of study are more likely to experience school-to-work transitions with high levels of income security. The effect of specificity are strongest and most positive for school-leavers at the highest level of upper-secondary vocational education (ISCED 354/MBO4). This level combines relatively high-level skills with strong connections to employers. In contrast to what I expected, I find that specificity has strong positive effects for more cyclically sensitive fields of study. As these findings contradict all theoretical expectations, I expect that two mechanisms could cause these findings. The first mechanism is a selection effect due to which only the best graduates from specific and cyclically sensitive fields have entered the labour market. The second mechanism is that fields that are in nature cyclically insensitive, such as education and health care, have been affected by the economic conditions as well, though not directly, but rather indirectly due to retrenchments or insufficient investments by the government during that period.

Chapter 4: Occupations and the non-standard employment career: How the occupational skill level and task types influence the career outcomes of non-standard employment
In chapter 4, I focus on the effect of occupational characteristics on the outcomes of non-standard employment, in particular the skill level and the task types of the occupations. Though occupations are a main determinant of employment outcomes according to sociological theory (Parsons, 1949), not much attention has been paid yet to how occupations influence the outcomes of non-standard employment. I expect that workers in occupations that require lower level skills or routine tasks are more likely to have careers with low levels of employment and income security, as they are more replaceable for employers. Information about workers' occupations was retrieved from the Dutch Labour Force Survey and linked to the typology that was created in chapter 2.

The results show that working in occupations that require high-level skills does not preclude precarious careers with low levels of employment and income security. Next to this, routine tasks do not have an unambiguous effect on the quality of the careers: routine cognitive tasks are more likely to result in careers with high levels of employment and income security, while routine manual tasks are more likely to result in careers characterized by non-employment. As non-routine manual tasks have no such effects, it is thus mostly the combination of routine and manual tasks that is most relevant for explaining employment outcomes rather than routine alone. This chapter thus confirms the importance of including occupations or their characteristics when trying to explain the outcomes of non-standard employment.

Chapter 5: Scarred by your employer? The effect of employers' strategies on the career outcomes of non-standard employment

In the final chapter, I focus on the main mechanism in the prospects and precarity scenarios: employers' strategies for using non-standard employment. Employers' non-standard employment strategies are likely to affect the outcomes of workers with non-standard employment contracts in their firms, but also to have an effect on the career path beyond the employment period at the firm: a non-converted non-standard contract can have a scarring effect on workers' future employment prospects. However, measuring employers strategies is complicated, as many employers do not have a thought-trough strategy for using non-standard employment, and those who say they do, might in practice have non-standard employment practices that do not align with the strategy they say they have (Hakim, 1990). Defining strategies as 'patterns in a stream of decisions' rather than predetermined plans (Mintzberg, 1978), employers' non-standard employment practices might reveal their actual strategies. Using aggregate employment register data, I construct firm-level indicators of non-standard employment practices: the share of fixed-term employment, the share of on-call employment, the transition rate from fixed-term to permanent employment, and excess mobility. Combined, these practices can give an image of the three main ways employers use non-standard employment: to screen workers, to be able to adapt their workforce, or to reduce costs.

The results show that workers who start their non-standard employment career in firms with screening strategies are most likely to experience careers with high levels of employment security, while workers in firms that use non-standard employment to reduce costs are more likely to experience careers characterized by low levels of employment and income security. Workers in firms that use non-standard employment to adapt their workforce are equally likely to have careers characterized by non-employment as workers in firms who use non-standard employment to screen in their workers. This means that strong scarring effects remain limited to firms that use non-standard employment to reduce costs.

1.5. Conclusions

1.5.1. Defining prospects and precarity with a processual approach

The first conclusion of this dissertation is that the quality of the outcomes of non-standard employment can be better defined using a multidimensional processual approach. By analysing career as continuous processes and taking into account simultaneously both the employment and income outcomes experienced during the trajectories, I was able to move beyond conclusions about averages (i.e. 'workers in non-standard employment earn lower incomes than workers in permanent employment') and traditional dichotomies between good and bad outcomes based on transitions to permanent employment. Instead, I could identify the large variety that also exists within the group of workers in non-standard employment, as well as in the group of workers who make the transition to permanent employment. Additionally, this dissertation clearly highlights the fact that permanent employment – which is considered the optimal outcome in many previous studies – does not necessarily have to be a final outcome, as quite some workers experience a career trajectory in which the permanent contract does not last. By assessing the employment security and income security that workers experience throughout their career trajectories, I bring a more nuanced definition of which outcomes are considered to offer prospects (those with high levels of employment and income security) and which outcomes are considered to be precarious (those with low levels of employment and income security).

1.5.2. Non-standard employment: prospect or precarity?

The second conclusion is that the title of this dissertation is the wrong question to ask. The first problem of this question is that it implies that only one of the options is true. The second problem is that it implies that these two options are the only options available. In this dissertation, I not only show that outcomes that offer prospects and outcomes that result in precarity exist simultaneously, but also that there is no dichotomy of two opposite states in which workers can be unambiguously classified. Instead, the outcomes of prospects and precarity should be seen as a multidimensional continuum with various gradations, in this case of employment and income security. To illustrate, I find that a significant group of workers cannot easily be classified into either of the two outcomes: some combine high levels of employment security with low levels of income security, while others combine low levels of employment security with high levels of income security. Again others have careers with intermediate levels of both types of security.

This large variety of outcomes of non-standard employment furthermore shows that labour market segmentation (Doeringer & Piore, 1971) is not limited to segmentation between workers in non-standard employment and workers in standard employment, but that it already exists within the group of workers who start in non-standard employment. Moreover, segmentation is certainly not a black and white divide, as several outcomes of non-standard employment cannot easily classified in terms of prospects or precarity. With traditional approaches focusing on transitions between employment statuses, 25% of the workers would be classified into either of the two outcomes, while in practice, their outcomes do not offer as many prospects or result in precarity as much as one would think based on employment status alone. Simply put, not all permanent employment offers prospects, and not all non-standard employment results in precarity. In the end, it is up to the workers in these careers to assess whether they think their careers offer prospects or are more precarious. As no measurements about workers' own job or career satisfaction are available, I refrain from classifying these outcomes but let them keep a middle ground. Taking on a processual multidimensional approach thus allows for nuancing and redefining the quality of employment, or actually, career outcomes.

The typology of outcomes of non-standard employment is furthermore found to be quite stable, not only via the replication strategy, but also when focusing on other groups or cohorts in the same context. The three typologies that were created in this dissertation for various cohorts and populations show great degrees of substantive similarity. Though the similarity of typologies is difficult to quantify, the substantive similarity of typologies indicates that the type of outcomes of non-standard employment are quite stable (see also Technical Appendix II). This offers opportunities as typologies of the outcomes of non-standard employment do not necessarily have to be made from scratch, but can also be based on previously created typologies. But more importantly, it shows that the variety in outcomes of non-standard employment is structural. When acknowledging the existence of this variety of simultaneously occurring outcomes, the main question should therefore better be: when does non-standard employment lead to more positive or more negative career outcomes?

1.5.3. Three perspectives on determinants of career outcomes of non-standard employment

By investigating the economic, sociological and human resources management perspectives on the outcomes of non-standard employment, this dissertation also draws conclusions with regards to this question. In particular, I look at explanations coming from three perspectives: the economic perspective, the sociological perspective and the human resource management perspective. I aimed to investigate how the mechanisms suggested in these perspectives affect the outcomes of non-standard employment. Here I discuss the conclusions I make based on the perspectives, and make suggestions for future research.

From the economic perspective, human capital theory proposes that education is an important factor of success in the career (Becker, 1993). In chapter 3, I indeed show that higher levels of education result in better outcomes of non-standard employment in terms of income security. Next to this, a stream of literature also suggests that the specificity of fields of study, which is linked to horizontal stratification of education, results in better employment outcomes as well (Bol, Ciocca Eller, Van de Werfhorst, & Diprete, 2019; Van de Werfhorst, 2004). However, I find that these positive effects of specificity are limited: the effect of specificity on the quality of school-to-work transitions is only evident and positive for levels of education that combine strong connections to employers with relatively higher level skills. Next to this, I did not find evidence that specific skills become a disadvantage in economic downturns. Apart from some minor methodological or policy-related explanations, this finding contradicts all main theories, but mimics results found in previous studies (Blommaert, Muja, Gesthuizen, & Wolbers, 2020; Muja, Blommaert, Gesthuizen, & Wolbers, 2019). This matter thus certainly deserves attention from future research, which I would encourage to try to repeat an analysis of the interplay between specificity and cyclical sensitivity, maybe using different cohorts in the analysis as well.

From the sociological perspective, I show in chapter 4 that not only the skill level of individuals matters for the employment outcomes, but also the skill level of the occupation itself and the types of tasks that are executed in occupations play a role. Though workers often select themselves or are selected into occupations that match their skill levels, occupations still have a modest independent effect on employment outcomes, with workers in higher skilled occupations having higher chances of careers with high levels of employment and income security. With regards to the types of tasks, the effects were not always in the expected direction, as not all routine tasks resulted in more precarious career types. Despite these unexpected results, this chapter clearly shows that demand-side characteristics, such as the types of occupations that employers are hiring in, also need to be taken into account in analyses of outcomes of non-standard employment. Though the routineness of tasks is an suitable method to include the concepts of both specificity as well as the monitoring costs related to occupations in analyses, direct measurements of these concepts per occupation could help further improving analyses of effects of occupations. Scales similar to the linkage scale that was used in chapter 3 to measure specificity of fields of study could also be used to measure specificity of occupations, and has also been applied as such in other research (Dekker, de Grip, & Heijke, 2002; Markus Klein, 2011). Measuring monitoring costs per occupation is probably more difficult, but can be a nice challenge for future research.

While occupations already somewhat brought in the demand-side effects on the outcomes of non-standard employment, the employer fully entered the equation when the human research management perspective was investigated in chapter 5. Here, I show that employers' strategies influence the outcomes of non-standard employment for workers. The findings place an important nuance to the trap scenario, as the employment outcomes for workers in firms with adaptability strategies are not as precarious as the theory would predict. Only cost reduction strategies have clear scarring effects on the career trajectories of workers in non-standard employment. This chapter furthermore shows that inferring strategies from employers' non-standard employment practices is a suitable approach as well, given that I found effects, whereas previous research focusing on stated employer motives often found effects to be limited (Hakim, 1990). In investigating the effects of employer strategies on workers' outcomes, it is likely better to use information on what employers actually do than on what employers say they do. I hope this dissertation inspires other researchers to employ similar strategies in their research.

It was beyond the scope and aim of this dissertation to compare the perspectives and to assess which of these is most relevant. Several determinants had to be taken from various data sources, and the separate relations between the determinants and the outcomes of non-standard employment already provided quite some innovation on previous research. The overlap between chapters is limited to the inclusion of level of education in all explanatory analyses. Though level of education appears to be one of the most important determinants of outcomes of non-standard employment, ranking the importance of educational specificity, occupational characteristics and employers' strategies is not possible. Though I would not want to start a battle between perspectives, it would be very interesting to know more about the contributions of these determinants to the outcomes of non-standard employment when included in one analysis. This would help identify which factors are most determinant of outcomes, which would subsequently help policy makers who aim to address labour market inequalities. I however need to leave this investigation to future research.

Another substantive limitation of this dissertation is the exclusion of workers who start working in self-employment. As the number of self-employed workers has also increased significantly in the last decades, it would also be very interesting to study their career development with a multidimensional processual approach. A multidimensional processual approach could potentially help to distinguish the voluntary self-employment from the more precarious, involuntary dependent self-employed workers. Though this will remain quite difficult with the data from the SSD due to the fact that self-employment is only registered on a yearly basis, researchers using other data on self-employment might benefit from applying a processual approach.

A final limitation of this study is that we can only take into account the employment status and income of workers in defining the quality of outcomes of non-standard employment. Though this already is a big step forward in assessing the quality of outcomes of non-standard employment compared to previous research, the quality of work is more than just the contract type and the income. The content of the work, workplace experiences, and room for self-development and initiative play a role in determining that quality of work as well (Roeters, Van Echtelt, Vrooman, Vlasblom, & Olsthoorn, 2021). These are more subjective characteristics that are not easily measurable and certainly not available in register data. Including such aspects in a processual approach is therefore likely to be difficult, and also was not possible in this dissertation. However, if researchers have (longitudinal) information available on more aspects of the quality of work, I strongly recommend them to include this information in the processual approach so the quality of outcomes of non-standard employment can be assessed even better.

1.5.4. Limitations and challenges of applying a multidimensional processual approach using multichannel sequence analysis

To apply a multidimensional processual approach, I used multichannel sequence analysis. I think that multichannel sequence analysis is a suitable approach for describing multidimensional longitudinal phenomena such as careers. With this approach, I have been able to create the more nuanced and stable image of the quality of outcomes of non-standard employment by analysing careers as full trajectories and by taking into account both the employment and income dimensions of careers.

Though sequence analysis is an extremely valuable method for describing labour market outcomes, there were some limitations in what I could and could not do with sequence analysis in this dissertation. A first limitation is that the clusters of the typologies are classified on the dimensions of employment security and income security, but these dimensions are not informing the statistical analysis – they are post-hoc interpretations. Attempts to include these dimensions in the empirical analysis, for instance by using conditional logistic regressions, have not been successful. It turned out that it was not possible to properly quantify these dimensions, in particular employment security, using the indicators I had at my disposal. In this dissertation, the concepts thus remain mostly qualitative indicators that help to make the large number of clusters from the typology manageable and interpretable.

A second limitation is that in sequence analysis, cause and effect are mixed into one outcome. For instance, the fact that someone transitioned from fixed-term employment to unemployment is likely to decrease their probabilities to make the transition to permanent employment at a later point in a career. That becomes all part of one sequence and is, in contrast to previous methods, taken into account. However, explanatory variables in this case can only explain that sequence as a whole. As it is impossible to include time-varying covariates in the current analysis, I cannot separately assess the impact of that transition to unemployment on the development of the rest of the career without splitting up the sequence, or for instance see whether transitions in the sequences are related to changes in any of the explanatory variables over time.

Next to these limitations, applying sequence analysis to large-scale register data is no neat feat either. During the analyses, I encountered a couple of challenges. First of all, with datasets as a large as the ones I used, it was impossible to analyse all cases simultaneously in one sequence analysis with the available computing power. As all sequences are compared to one another, a matrix of size n^2 needs to be created. For chapter 2, this would require a matrix of $680{,}180^2 = 462{,}644{,}832{,}400$ cells. Many computers will then simply say no. Mine at least did. One could opt for using one subsample instead, but due to the large heterogeneity of the data, the choice of subsample was also highly determinant of the outcomes of the sequence analysis.

As a work-around, I developed a replication strategy that allows for analysing all sequences in different subsamples (see Technical Appendix I). Though this procedure provides a very valuable method via which not only all sequences can be included, but also the robustness of the typology can be established, this strategy also highlights other issues that arise when applying sequence analysis to large-scale register data. Though I believe that the register data from the SSD are the best and most interesting data available to study career trajectories, they provide a temping level of detail. My choice to have a large number of states and long sequences, as well as the existence of measurement error (Pankowska et al., 2020), have as a consequence that the data are also very heterogeneous. As a result, all typologies I created still consisted of clusters with quite of lot of within-cluster heterogeneity. Due to this within-cluster heterogeneity, I was not able to use any of the cluster quality measures, as they never reached any acceptable levels for any reasonable number of clusters (<25 clusters). This had as a consequence that determining the optimal number of clusters for the typologies for the subsamples as well as for the overall typology ended up being a somewhat subjective process, constantly assessing as a researcher whether one additional cluster added substantive value to the typology or not. Though this approach is not necessarily less valid than relying on quantitative cluster quality measures (Cornwell, 2015), I have perceived this to be a challenging part in the creation and validation of my typologies, as can be read in my extended discussion of the creation of the typology for chapter 5 (see Technical Appendix II).

Other than the typologies resulting from a subjective procedure, some might also object to the classification of sequences into clusters, and throwing away information by doing so. Though I have not used this approach in this dissertation, one potential solution could be to not treat clusters as separate categories, but to use the similarity of each sequence compared to the cluster medoid as a dependent variable in Dirichlet regressions (Hijazi & Jernigan, 2009). This way, one could be able to better take into account the fact that not all sequences are equally homogeneous in the clusters and might also resemble other clusters to some extent. Next to this, one could step away from analysing sequences in clusters, but rather focus on sequence complexity measures instead (Elzinga & Liefbroer, 2007; Pelletier, Bignami-Van Assche, & Simard-Gendron, 2020). However, I feel that by focusing on separate complexity measures, the processual aspect of sequence analysis, which is its major advantage, gets somehow lost and you lose the rich picture of how non-standard employment works in the career.

Finally, the large typologies resulting from my sequence analyses confronted me with some additional challenges. In general, interpretation of the results of (multinomial) logistic regressions is more challenging that interpreting the results of OLS regressions. Having dependent variables with 14 to 17 categories makes interpretation of these results even more challenging, especially when there is a multi-dimensional relationship between the outcomes. Marginal effects provided a solution to these interpretation issues (Mize, 2019), but worsened the issue of computing time that was discussed above. The duration of the calculation of marginal effects based on that multinomial logistic regression increases exponentially with the number of outcome categories and the number of variables included in the regression. To illustrate: the calculation of the marginal effects for the four interaction effects of chapter 5 for instance took around two days. Per interaction. One can thus say that the explanatory analyses of the typologies have been a great exercise in patience.

Several of these limitations and challenges are particular to this dissertation and the choices I made. Other researchers using less heterogeneous data, with fewer cases, fewer possible states, shorter sequences and smaller typologies are likely to have an easier experience doing sequence analysis. However, with less detailed data, the results are also likely to be less rich and nuanced. Moreover, this dissertation shows that with quite some perseverance and patience, these limitations can be overcome. As increasing numbers of researchers are applying sequence analyses in social sciences, many researchers are also working hard to improve the method and to create new functionalities for the method (e.g. Liao & Fasang, 2021; Pelletier et al., 2020; Studer et al., 2018, and many others from the Sequence Analysis Association). With my replication strategy (Technical Appendix I), I furthermore hope to have made a modest methodological contribution that could be useful for other researchers who struggle with creating representative typologies with large-scale data.

All in all, though adopting a multidimensional approach comes with challenges, I still recommend future researchers to certainly consider using it, potentially with multichannel sequence analysis, for studying longitudinal phenomena, and in particular careers. With a processual approach, you get more nuanced outcomes, and with that, a better understanding of to what extent and when non-standard employment offers prospects or results in precarity.

2

A multichannel typology of temporary employment careers in the Netherlands

Identifying traps and stepping stones in terms of employment and income security

Abstract

In this chapter, we apply multichannel sequence analysis of labour market positions and incomes to create a typology of careers starting with temporary employment in the Netherlands. For this purpose, we use detailed register data from Statistics Netherlands for all workers who entered temporary employment in 2007 and were observed for 96 months. This approach leads to a typology of 17 different career types that shows a considerably larger variation - in terms of employment and income security - than previous research has shown. Specifically, the typology shows that 29.6% of the research population has a stepping stone career with high employment and income security, while 39.7% has a dead-end career with low employment and income security. However, a large part of careers – 24.7% – cannot be classified in this traditional distinction, as they combine high employment security and low incomes or high incomes and low employment security.

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Due to reviewer requests, this chapter uses the term ‘temporary employment’ rather than ‘non-standard employment’.

2.1. Introduction

Temporary employment is a widely discussed topic both in research and policy. In the Netherlands, the share of temporary employment has considerably increased during the last 20 years: while in 2003 14% of the working population was employed in a temporary contract, this percentage increased to 22.7% in 2017 (CBS Statline, 2018a). In contrast to other European countries, this increase has persisted even after the peak of the recent economic crisis (Eurostat, 2021c; Euwals, De Graaf-Zijl, & Van Vuuren, 2016).

A large body of research has examined the causes and the consequences of the rise in temporary employment. This form of employment presents advantages for employers as it offers them flexibility in adapting their workforce. In contrast, for workers, jobs with temporary contracts are in general considered to be inferior (De Beer, 2016; Vermeulen, De Wit, Van Leest, & Rossen, 2016). Specifically, workers in such jobs, on average, earn lower wages, enjoy less job security, have fewer promotion possibilities and receive less fringe benefits and training (Booth et al., 2002; Giesecke & Groß, 2003; OECD, 2014). For this reason, temporary employment is seen as a source of rising social inequality (Gash & McGinnity, 2007), while, in the context of labour market segmentation theory, the permanency of the contract is core in distinguishing between the primary and the secondary segment of the labour market (Fuller & Stecy-Hildebrandt, 2015; Gash, 2008; Kalleberg, 2001; Scherer, 2004).

Research is inconclusive about the role of temporary employment in the employment career. Some find that temporary jobs function as a stepping stone towards permanent employment (De Graaf-Zijl et al., 2011; De Lange et al., 2013), whereas others suggest that temporary employment hinders career progress as individuals get trapped in a vicious circle of insecure jobs and non-employment (Leschke, 2009; McGinnity et al., 2005). We argue that four characteristics of previous research may be responsible for this inconclusiveness. First, most studies typically focus on transitions from a specific type of temporary employment – typically fixed-term contracts - and in this way fail to account for differences between the various types of temporary employment contracts. Second, research focuses almost exclusively on specific point-in-time transitions – usually the transition to permanent employment –, ignoring the timing, order and duration of all other employment and non-employment spells that individuals experience in their careers. Third, employment with a permanent contract is strictly considered as the only 'optimal' outcome of a career path. Fourth, studies typically investigate the quality of the employment career by looking at a single aspect of it – typically the type of contract or income (see for example, D'Addio & Rosholm, 2005; Remery, van Doorne-Huiskes, & Schippers, 1999; Steijn, Need, & Gesthuizen, 2006), while we know that the quality of the employment career is better assessed by studying these aspects simultaneously (Tilly & Tilly, 1998).

This chapter uses a holistic approach to investigate temporary employment. Specifically, building on the seminal work of Fuller and Stecy-Hildebrandt (2015), we apply multichannel sequence analysis (Gabadinho, Ritschard, Studer, & Nicolas, 2011; Gauthier et al., 2010) to simultaneously study employment and income trajectories of individuals who enter temporary employment. Employment trajectories are created by taking into account spells of several types of temporary employment, i.e. fixed-term contracts, on-call contracts and temporary work agency contracts, as well as spells of self-employment and non-employment. In this way, two aspects of job quality, i.e. employment and income, are combined to produce a typology of temporary employment careers. This allows us to further classify the clusters of temporary employment trajectories according to the employment and income security they offer to workers. This classification is much more detailed than previous research as the type, the timing, the duration and the order of all employment spells and the incomes of individuals are taken into account in the creation of the typology. This chapter also delivers a modest methodological contribution to sequence analysis. Specifically, within our multichannel sequence analysis, we propose a replication strategy that ensures the reliability of typologies when dealing with large-scale, heterogeneous data.

This chapter is organized as follows: section 2.2 discusses the theoretical approaches on the role of temporary employment in the life course. Section 2.3 presents the methodology of multichannel sequence analysis, the data that we use and the proposed replication strategy. Section 2.4 presents the typology of temporary employment careers and section 2.5 the conclusions of this research.

2.2. Temporary employment as a stepping stone or a trap

Temporary employment falls under the broad concept of labour market flexibility. Labour market flexibility refers to a wide array of contracts and work arrangements that deviates from employment with a permanent contract that entails an 8-hour working day. Research on labour market flexibility distinguishes between numerical and functional flexibility (Atkinson, 1984; Hunter, McGregor, Maclnnes, & Sproull, 1993; Kalleberg, 2001; Smith, 1997). *Numerical flexibility* refers to the types of flexibility that are based on changes in the size of the workforce of the firm. *Functional flexibility* refers to the extent that workers can change tasks and activities within the firm. Within numerical flexibility, research distinguishes further between external and internal flexibility. *External numerical* *flexibility* refers to the adjustment of the number of workers employed by the firm using resources from the external labour market. Forms of temporary employment, such as fixed-term contracts or hiring workers via a temporary work agency, fall in this category of flexibility. *Internal numerical flexibility* refers to the adjustment of working hours within the firm without turning to the external labour market. Part-time employment as well as some forms of temporary employment, such as on-call work, are examples of this type of flexibility. Studying the quality of employment careers universally would have to take into account all the aforementioned types of labour market flexibility, together with income and job satisfaction. These three aspects are identified in the literature as the core aspects of job and career quality (Kalleberg, 2011).

The Netherlands are a particular case when it comes to labour market flexibility, as various forms of numerical flexibility are much more common in the Dutch labour market compared to other European countries. The Netherlands have experienced a large and persisting increase of fixed-term employment in the last two decades: 21.7% of employees now work on a fixed-term contract, while the EU average is only 14.3% (Eurostat, 2021d). This increase is due to the relatively strong employment protection of permanent contracts while the protection of fixed-term contracts is relatively low, which makes using fixed-term contracts attractive for employers (OECD, 2013). The shares of temporary work agency contracts and on-call jobs have increased in this period as well, with the share of on-call jobs doubling to 6.3% in 2017 (CBS Statline, 2018b).

Furthermore, the Netherlands are well-known for their high share of part-time employment: 46.6% of the working population and 74.1% of working women work part-time in the Netherlands, while the EU averages are only 18.7% and 31.1% respectively (Eurostat, 2021c). However, in the Netherlands, part-time work can be hardly considered as a form of employment that may have negative consequences for the career of the individual. Working part-time is mostly a voluntary choice of the employees, for instance to facilitate workers in combining work and care tasks (Portegijs & Keuzenkamp, 2008). Furthermore, Dutch employment legislation allows workers to adapt the number of their working hours (Hevenstone, 2010). For this reason, the Netherlands have one of the lowest shares of involuntary part-time employment in Europe (Eurostat, 2021b): in 2017 only 16.6% of part-time employees indicated they would prefer to work more hours (CBS Statline, 2021b).

In this chapter, we focus on the most common types of temporary employment in the Netherlands. These include fixed-term contracts and temporary work agency jobs that are forms of external numerical flexibility as well as on-call jobs that is a form of internal numerical flexibility (De Beer et al., 2011). Seen from the broad perspective of labour market flexibility, the latter two forms of employment create insecurity for the worker that extends beyond the duration of the employment contract. Specifically, on-call work is associated with insecurity in working hours and therefore also in income, while temporary agency work is related to insecurity with some employment and income insecurity but also with the workplace where temporary agency workers are employed. Therefore, although in some cases on-call jobs and temporary work agency jobs may be permanent, the negative aspects that are related to these contracts persist.[3]

In research on the role of temporary employment in the employment career, there are two opposing scenarios. More specifically, the typical aim of this research is to determine whether temporary employment functions as a *stepping stone* – a portal to permanent employment – or as a *dead end* or *trap* – a job that leads to repeated temporary jobs alternated with unemployment. The stepping stone scenario is based on human capital theory (Mincer, 1974), which suggests that by working in temporary employment instead of remaining unemployed, workers acquire skills and experience which subsequently improve their career prospects, in terms of both income and contract type (De Graaf-Zijl et al., 2011). Signalling theory, which incorporates imperfect information into human capital theory (Becker, 1993; Spence, 1973), supports the stepping stone scenario. This theory suggests that employers possess imperfect information on the productivity of new hires and use temporary jobs as a screening device during the probation period (Weiss, 1995). If the worker meets the employer's expectations, the employer offers the worker a permanent contract (Booth, Fancesconi, & Frank, 2002; Faccini, 2014; McGinnity, Mertens, & Gundert, 2005; Reichelt, 2015).

Those who argue that temporary jobs are dead ends use arguments from dual labour market theory (Doeringer & Piore, 1971) and argue that these contracts are used by employers mainly to adapt their workforce to economic fluctuations. With temporary employment contracts, employers can hire workers easily in an economic upturn, and lay them off at low transaction costs when product demand decreases (Kalleberg, 2003). As employers hire workers for a short period of time, they have fewer incentives to invest in workers' human capital. Therefore, an employment history that includes several spells of temporary employment can function as a signal of lower productivity for future employers, making them less likely to offer the worker a permanent contract (Berton et al., 2011; Esteban-Pretel, Nakajima, & Tanaka, 2011; Hopp et al., 2016; Hudson, 2007).

Many empirical studies have investigated the labour market outcomes of temporary employment. However, this research has not reached a uniform outcome: some studies

3 We estimate that around 20% of the records indicating on-call work involves a permanent contract, while only 3.5% of the records indicating temporary agency work involves a permanent contract. Unfortunately, no official statistics exist on this subject.

find that temporary jobs function as stepping stones, whereas others conclude that they lead to traps of repeated temporary jobs and unemployment spells. Several factors explain this inconclusiveness. Firstly, many studies disregard the variation in types of temporary employment contracts. Many lump all different types of temporary employment together (D'Addio & Rosholm, 2005; De Graaf-Zijl et al., 2011; Esteban-Pretel et al., 2011; McGinnity et al., 2005; Remery et al., 2002; Steijn et al., 2006). Others focus only on one specific type of temporary employment, typically fixed-term contracts (Autor & Houseman, 2010; Hopp et al., 2016; Ichino, Mealli, & Nannicini, 2008; Pavlopoulos, 2013), while in some cases the type of temporary employment that is studied is not clearly defined (Faccini, 2014; Giesecke & Groß, 2003; Picchio, 2008; Wolbers, 2010). If any variation in the types of temporary employment is allowed, this is mostly limited to the distinction between fixed-term contracts and seasonal/casual work, which are then studied separately (Addison, Cotti, & Surfield, 2015; Booth et al., 2002; De Lange et al., 2013; Leschke, 2009). A notable exception is the study by Berton et al. (2011) in which the interplay of the effects of five types of temporary employment is studied.

Research shows that Dutch employers use different types of temporary employment for different reasons (Van Echtelt, Schellingerhout, & De Voogd-Hamelink, 2015). In more detail, employers for instance tend to use fixed-term contracts either as a probation period for their new hires or because they are uncertain about future product demand. The first aim may cause a stepping stone effect, as a successful probation period would lead to permanent employment. The second aim can have varying outcomes, depending on the economic context: in an economic upturn, the fixed-term contract may be converted to a permanent contract as future demand is quite secure, but in an economic downturn the contract is less likely to be followed by a permanent job. Temporary work agency workers and on-call workers are mostly used by employers to get more flexibility to adapt their workforce to short-term or frequent fluctuations in demand. On-call workers are furthermore used to replace sick or absent workers. In such types of jobs, it is less likely that a contract is converted into a permanent contract (Berglund, Hakansson, Isidorsson, & Alfonsson, 2017). As the possible outcomes of temporary employment turn out to depend strongly on the type of temporary employment, the fact that this variation has not been included in previous research may have contributed to the inconclusiveness of the results.

Secondly, previous research typically studies point-in-time transitions and focuses on the duration until a transition to permanent employment takes place. This means that there is little attention for what happens *until* that specific transition occurs, and for what happens *after* this transition is made. This introduces a twofold problem. First, as temporary employment may have a scarring effect, the career path of a worker is likely to influence a worker's probability to make the transition to a good labour market outcome as well as the duration until that transition takes place (Hopp et al., 2016; Mooi-Reci & Dekker, 2015; Pavlopoulos, 2013; Scherer, 2004). Second, a transition to permanent employment does not have to be a final outcome in the worker's career. Especially in times of crisis, jobs with permanent contracts may be terminated as well. Furthermore, some workers may be willing to trade job security for an higher income or more working hour flexibility and opt for moving from a standard to a temporary job (Van Der Klein et al., 2016).

A third issue is that employment with a permanent contract is regarded as the only 'good' outcome of a career. However, given the variety in temporary employment, not all temporary jobs have to be an inferior labour market outcome *per se*: some workers in temporary jobs may earn sufficiently high wages that compensate for the job insecurity that accompanies temporary employment. The opposite reasoning is also valid: some workers may make the transition to a permanent job, but still not earn a decent living wage, resulting in in-work poverty (Thiede, Lichter, & Sanders, 2015). In this case, income insecurity detracts from employment security. By considering employment with a permanent contract as the only good outcome without looking at the incomes of both permanent and temporary jobs, the image of temporary employment outcomes probably becomes distorted.

The fourth and final issue refers to the fact that the distinction between successful and precarious careers focuses typically on one aspect of job quality, either labour market positions or income. Research suggests that job quality can be effectively assessed by three factors: labour market position, income and job satisfaction (Kalleberg, 2011; Tilly & Tilly, 1998).

Some of the aforementioned issues of previous research have been dealt with in the seminal study of Fuller and Stecy-Hildebrandt (2015) on Canadian workers. By using sequence analysis on labour market positions and by distinguishing between fixed-term contracts and part-time employment, they adopt a holistic approach on employment careers which delivers a clear image of the variation of temporary employment careers in the Canadian labour market. They show that a large share of workers is unable to remain in jobs with permanent contracts and return to temporary employment. However, although they investigate income growth in different career types, income is not included in the construction of their typology of employment careers. Thus, there might still be quite some variation within the career types in terms of income, and consequently also in terms of precarity. Despite this, their work has clearly illustrated that using a holistic approach yields valuable insights in the consequences of temporary employment on the employment career development that cannot be provided by transition-based approaches. Building upon the work of Fuller and Stecy-Hildebrandt, we adopt a holistic career approach to study the quality of employment careers by using multichannel sequence analysis on labour market positions and income in the Netherlands. Using this method, the aforementioned four issues of previous research can be tackled. First, we take into account heterogeneity in temporary employment –more than previous research has done – by distinguishing between fixed-term contracts, temporary work agency jobs and on-call jobs. Secondly, sequence analysis allows us to study employment careers by taking into account the number and type of transitions that are made, the duration of every spell of employment contract and non-employment, as well as and the order in which these spells emerge in the career, rather than focusing on point-in-time transitions. Thirdly, permanent employment is not considered the only optimal outcome as we also take into account the income of the job and the possible labour market transitions that occur *after* the transition to a permanent contract. Finally, we simultaneously study the employment trajectories and the income of workers. This allows us to evaluate the quality of careers at the level of employment and income security (Bolhaar, Brouwers, & Scheer, 2016). In this way, we can better distinguish between successful and precarious employment careers and therefore get a detailed picture of the extent to which temporary employment is a stepping stone or a trap in the Dutch labour market.

2.3. Data and methodology

In this chapter, we aim to create a typology of employment careers that resemble each other on the basis of labour market positions and income. Sequence analysis is a statistical method that is appropriate to fulfil the aforementioned aim as it allows us to study temporally ordered sets of events and to cluster them based on similarity. As we want to create a typology of temporary employment careers on the basis of two types of states, labour market position and income, we use multichannel sequence analysis (Cornwell, 2015; Gauthier et al., 2010).

Sequence analysis is a statistical method that aims primarily at describing a series of events or states. Specifically, it measures the similarity of different trajectories that are present in the data and, on the basis of this similarity, classifies trajectories into clusters. Contrary to other statistical methods that are used in life course research, such as event-history analysis, sequence analysis does not aim at detecting causal relationships (Abbott & Tsay, 2000). Some may consider this a strong disadvantage (Levine, 2000; Wu, 2000), which may account for the relatively limited number of applications of this method in social sciences. However, we concur with Abbott & Tsay (2000) who claim that description is a valuable but too often overlooked part of social science research. As sequence analysis shows, the various strings of events that occur give a more detailed picture of employment careers than more traditional methods such as transition tables, that only depict the situation on certain points in time, or Kaplan-Meier plots, that only show the cumulative occurrence of one specific event, such as the transition to permanent employment.[4]

Sequence analysis has its origin in genetics for the purpose of studying DNA sequences, but is increasingly being used in the social sciences for studying longitudinal phenomena, such as by Scherer (2001), Elzinga & Liefbroer (2007) and Aisenbrey & Fasang (2017). To our knowledge however, the only study that has applied sequence analysis to study temporary employment to date is Fuller and Stecy-Hildebrandt (2015).

The key concept in (multichannel) sequence analysis is the similarity of sequences. The most widely used method to determine this similarity is *Optimal Matching* (Abbott & Forrest, 1986; Abbott & Tsay, 2000). To determine the similarity of sequences, this method takes into account the number of substitutions and permutations that are needed to make two sequences identical. Each change (i.e. substitution or permutation) is assigned a cost according to the judgement of the researcher. Specifically, to make certain sequences more distant than others, one can decide to make certain changes more 'expensive' than others. However, Optimal Matching does not take into account the timing of transitions in the determination of similarity. This is an important disadvantage as timing is a very important aspect of careers, especially when studying labour market transitions: a career in which a transition to permanent employment occurs after six months differs considerably from a career in which that transition occurs after 60 months. Optimal matching is rather insensitive to such timing differences, as it allows for aligning sequences by inserting and deleting states (Studer & Ritschard, 2016). This could have as a consequence that such careers are classified as similar, while they substantively differ from each other. To make our analysis more sensitive to timing differences, we use a *Hamming distance* cost setting with constant substitution costs (Hamming, 1950). The Hamming distance does not allow for inserting and deleting states by assigning extremely high costs to such changes, which means that sequences can only be aligned by substituting states. This prevents important labour market transitions from being moved either forward or backward in time when determining the similarity of sequences. This means that timing is prioritized (Studer & Ritschard, 2016).[5]

4 Sequence analysis can be part of a causal analysis, as the resulting typology resulting may be used as a dependent variable in order to predict which kind of factors lead to a certain type of sequence. In this paper, the focus lies on creating a typology of temporary employment trajectories itself that can be used in future research for causal analysis.

5 The *Dynamic Hamming distance*, which is an extension of the Hamming distance that allows for time-varying costs based on transition rates, was considered for the analyses as well. However, as determining costs based on transition rates is disputed (Studer & Ritschard, 2016) and the final results did not substantively differ from the results obtained using the regular Hamming distance, the latter was used.

In multichannel sequence analysis, two or more channels per individual are studied simultaneously. This means that the channels are linked, which in our case means that the labour market position of person 1 in time point 1 in the first channel occurs at the same time as the income of person 1 in time point 1 in the second channel. This multichannel nature complicates the determination of the similarity of sequences. Multichannel sequence similarity is determined following the approach of Pollock (2007). In this approach, the states of the two channels are first combined into a new sequence consisting of “multi-states”. In this approach, the states of the two channels (A and B) are first combined into a new sequence consisting of “multi-states”. In every time point the state of this new sequence is defined as the combination of the states of the two channels in the same time point (AB). Second, we proceed by determining the similarity of the new sequences. This is done by summing the substitution costs of the separate channels. For example, if the cost of moving from state A_1 to state A_2 is 1 and the cost of moving from state B_1 to state B_2 is 2 then, in the new sequence, the cost of replacing multi-state A_1B_1 for multi-state A_2B_2 is 3. The multichannel sequence analysis is conducted in the statistical software R (R Core Team, 2019) using the TraMineR package (Gabadinho, Ritschard, Studer, et al., 2011) and the WeightedCluster package (Studer, 2013).

2.3.1. Data

The data that are used come from a dataset that was constructed by Statistics Netherlands with the specific purpose of studying the dynamics of temporary employment. This dataset is a subset of the basic integral registration dataset (‘*System of social statistical datasets’* – *SSD*) that contains micro level register data on welfare, jobs and other characteristics for all individuals who are registered in the Netherlands. These data have been collected by Statistics Netherlands combining information from the basic integral registration (‘Polisadministratie’), from the Dutch tax administration (‘Belastingdienst’) and the Dutch Employee Insurance Agency (‘UWV’) (Bakker et al., 2014). The subset on temporary employment contains information about the labour market position of all individuals aged between 15 and 74 who have started working in temporary (dependent) employment as from January 2007 (De Vries, Michiels, & Gringhuis, 2017). People who were already in temporary employment during the three months before January 2007 are not included in the dataset. For the purpose of this study, we retained individuals who entered temporary employment between January 1st 2007 and December 31st 2007. These individuals can be followed until December 2015, allowing us to study individuals for 96 months. The records contain exact information – including the start and end dates – on employment status, contract type and (un)employment spells. All records that were shorter than one month are merged into monthly observations, prioritizing the record with the longest duration, which results in a dataset with 96 monthly episodes for every person. Although the 8-year period does not cover complete employment careers, our data offer a highly detailed time window that can be studied holistically to represent the employment career. The dataset with employment careers is linked to income records collected by the Dutch tax office that are also available in the main dataset (SSD). These income records contain information on income from paid employment, self-employment as well as income from benefits.

Student jobs are filtered out by selecting individuals who were not enrolled in education at the moment they entered temporary employment. Also individuals aged under 18 (compulsory schooling age) at the moment of starting temporary employment are fully excluded from the sample. Individuals who receive old age pension benefits, a surviving dependant's pension or annuities for at least 12 months in the observation period are excluded from the sample. This selection mostly excluded older individuals who were close to the retirement age or who benefited from early retirement. Individuals aged over 60 at the moment of starting temporary employment are fully excluded from the sample. Finally, only individuals who could be observed for 96 months are included, which for instance excludes persons who emigrate or decease. All the aforementioned selections resulted in a dataset consisting of 680,180 individuals. As we had insufficient computing power[6] at our disposal, we use a replication strategy using 6.5% random samples to come to a reliable typology. This replication strategy is discussed in section 2.3.3.

Since the dataset only includes individuals who have entered temporary employment in 2007, some issues of selectivity may arise in our study. First of all, we have no information about the career paths of individuals who never enter temporary employment. It is likely that the characteristics of these individuals differ from the characteristics of the individuals who do enter temporary employment. However, as we want to focus on the career after entering temporary employment, the group of individuals who never enter temporary employment is not relevant to our research. Second, we only observe careers from the moment the individual enters temporary employment. Unfortunately, we have no information on the employment history of individuals. This does not pose any problems for the creation of the typology, but may introduce some bias when further research attempts to predict cluster membership on the basis of our typology.

2.3.2. Variables

The variables that are used to create the multichannel sequences are labour market position and income. The variable labour market position for the first channel is based

6 Running an analysis on 680,180 sequences of length 96 would require an extremely powerful computer, as a matrix of 680,180 by 680,180 would have to be created.

upon two main variables: type of contract and socio-economic position in a given month. The type of contract distinguishes between permanent contracts, fixed-term contracts, temporary work agency contracts, on-call *contracts and* interns. However, as the number of interns was very small (<0.5%) this group was merged with fixed-term contracts. Temporary work agency workers and on-call workers may be employed on a permanent contract. However, they are still classified in the respective categories of temporary employment as these workers, despite their permanent contracts, have insecurity in terms of the location of employment or working hours.

Within the group of individuals who were not in dependent employment, we distinguish between self-employed, unemployed, those on non-work related benefits, students, retired and a group of all other states. Individuals are considered self-employed only when their largest income source is self-employment. Unfortunately, we cannot observe people who combine dependent employment and self-employment.[7] Due to the restrictions that we applied, the number of individuals receiving a pension benefit was very small (<0.5%). Therefore, this group is merged into the state ‘other’. Actually, the state ‘other’ is very heterogeneous, as apart from those receiving a pension benefit, it also includes inactive individuals and individuals with an unclassified labour force status. In total, we distinguish between nine possible states for the labour market position in the sequence analysis (see Table 2.1).

Table 2.1: Categories of sequence variables

Labour market position	**Gross monthly income (in €)**
Permanent contract	No income
Unemployed	1-250
Social benefit	251-500
Student	501-750
Other	751-1000
Self-employment	1001-1250
On-call work	1251-1500
Temporary work agency employment	1501-1750
Fixed-term contract	1751-2000
	2001-2500
	2501-3000
	3001-4000
	4000+

7 When an individual is in the payroll of a company, (s)he is always registered as an employee, even if (s)he is actual owner of the company.

The second channel of the sequence analysis is based on monthly individual income from the main job or, in case of non-employment, income from benefits. In both cases, this refers to gross income, excluding special payments and bonuses. For the self-employed, we rely on information about their yearly income, which they provide in their yearly earnings statements to the tax office. These incomes are divided by the number of months in self-employment in the year to get the monthly income from self-employment. The income of the self-employed includes also income from other activities, such as freelancing (19.9% of the records).[8]

As sequence analysis treats all states as discrete and computes costs for each state combination, it is not possible to include income as a continuous variable. Therefore, individual monthly income is classified into 13 categories (see Table 2.1). In this classification, we use a smaller range for lower income groups and a larger for higher income groups. The reason for this choice is that an income fluctuation of €250 is likely to have larger consequences for persons receiving a lower income (e.g. €750) than for persons receiving a high income (e.g. €2500).[9] As career quality is not only influenced by income level but also by income stability, we want to allow for such fluctuations to affect the analysis.[10]

8 The measurement of the income of the self-employed is far from ideal for several reasons. First, monthly income for this group is an average coming from the yearly income and therefore it is far from an accurate approximation of the real monthly income from self-employment. Second, we do not observe capital income, which can be an important source of income for the self-employed. Furthermore, the self-employed may re-invest parts of their profits into their company. Finally, the self-employed may benefit from fiscal creativities to lower their incomes. Combined, these disadvantages are likely to lead to an underestimation of the incomes of the self-employed. Furthermore, we do not have information on the incomes of directors/large shareholders and family workers. Results concerning the self-employed should thus be interpreted with care.

9 For reference, the modal monthly income in the Netherlands varied from €2400 in 2007 to €2700 in 2015.

10 There are several other reasons why we have decided to use this number of income brackets. First of all, in contrast to what we would expect, reducing the number of income categories did not lead to a reduction of the final number of clusters in the typology. Second, if we would take larger income categories, such as income quintiles, not only would we miss substantive income fluctuations in the lower ends of the income spectrum, but the clusters of a resulting typology would be more homogeneous in terms of income than in terms of labour market positions, as it would become easier to align sequences based on income than on labour market positions. This would make it much harder to classify clusters in terms of employment security. Furthermore, as we strive to get an image of the extent to which temporary employment functions as a stepping stone or trap, we prefer to achieve more homogeneity based on labour market positions than on incomes. Though channel weights could be used for this purpose as well, we feel that the choice for any channel weights would be arbitrary, whereas our choice for the income categories is substantively founded.

2.3.3. Clustering: a replication strategy

Sequences are clustered with a Ward clustering (Ward, 1963). However, determining the number of clusters was a complex matter. The existing objective measures for the determination of the optimal number of clusters are based on the homogeneity of sequences (Studer, 2013). In our data, there is considerable sequence heterogeneity: for example, within the 44,571 sequences of sample 1, 44,265 are unique. This is due to the large number of states in both channels and the sequence length. Therefore, in our case, the minimum cluster quality standards of these objective measures were never met, not even closely.

In cases where the objective measures of determining the optimal number of clusters are not applicable, a different approach needs to be developed. Therefore, we designed a replication strategy that can be used to deal with extremely heterogeneous sequences and get a reliable clustering solution. This strategy is inspired by the bootstrapping method proposed by Hennig (2007) but differs from it in two ways: first, whereas Hennig's method allows for sampling with replacement within the data that is used for the sequence analysis, our replication strategy draws a limited number of equally sized random samples without replacement from the population of 680,180 individuals. Second, our replication strategy does not rely on quantitative measures to determine cluster reliability, but focuses more on the similarity in the substantive interpretation of the clusters. This qualitative aspect of the method allows for dealing with heterogeneous sequences, as quantitative measures are of little use for such heterogeneous groups. However, this qualitative method involves a time consuming process as we have to provide a substantive interpretation to several clustering solutions. Therefore, the replication strategy proposed here is preferable to Hennig's original bootstrapping method only when quantitative measures cannot be used and when computational limits prevent the use of large-scale data.

Table 2.2: Replication strategy: relative sizes of clusters occurring in the 17-cluster solutions per sample

		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6	Sample 7	Sample 8	Sample 9	Sample 10	Count
	Number of cases	44571	44106	44525	44373	44072	44405	44349	44296	43703	44655	
1	Comfortable Careers	6.42%	5.28%	4.14%	3.78%	3.90%	5.93%	4.62%	5.83%	4.98%	5.71%	10
2	Prospects Pronto	5.76%	6.47%	7.52%	5.54%	6.38%	6.20%	5.83%	5.15%	2.83%	5.38%	10
3	Swift Security	6.60%	5.59%	9.02%	7.36%	6.62%	6.65%	5.66%	6.81%	4.30%	5.93%	10
4	Common Course	4.06%	6.94%	6.66%	4.53%	5.99%	6.58%	5.34%	6.01%	7.83%	6.57%	10
9	Shift to Self-employment	7.17%	6.76%	7.56%	7.22%	6.99%	7.44%	7.64%	7.71%	7.36%	7.60%	10
10	Passing Permanency	4.93%	8.83%	5.24%	6.99%	3.84%	7.99%	4.21%	6.18%	3.42%	6.31%	10
12	Ongoing On-call	3.25%	3.08%	4.00%	1.46%	3.15%	2.02%	2.36%	2.79%	1.89%	2.24%	10
15	Way to Welfare	11.85%	11.36%	9.69%	10.82%	10.58%	7.67%	7.91%	10.87%	11.56%	10.96%	10
16	Itinerary to Inactivity	3.34%	3.47%	2.36%	4.51%	2.60%	2.52%	3.44%	4.09%	4.23%	4.83%	10
17	Unfortunate Unemployed	3.75%	4.13%	3.90%	3.43%	3.60%	3.65%	4.28%	3.41%	3.97%	4.15%	10
7	Precarious Permanency	5.30%	5.91%	6.97%	7.05%	7.90%	4.84%	x	4.76%	4.67%	6.10%	9
14	Inactive Intermezzo	6.26%	3.88%	3.51%	x	7.91%	7.60%	3.05%	6.90%	4.49%	x	8
11	Forever Flexible	11.57%	7.42%	13.66%	7.88%	x	x	9.89%	x	10.13%	8.98%	7
5	Moderately to Modesty	4.48%	x	3.86%	x	x	x	9.07%	6.02%	9.95%	4.82%	6
13	Temporary Work Agency Track	3.63%	5.39%	3.21%	x	3.96%	x	x	3.25%	4.64%		6
6	Regular Route	7.73%	8.94%	x	7.29%	5.55%	7.11%	x	x	x	x	5
8	Fortunate Fixed-term	3.91%	4.89%	x	x	6.67%	x	x	6.38%	6.19%	x	5
*	Careers with a short period of inactivity	x	1.66%	4.48%	x	x	x	3.11%	x	x	5.08%	4
*	Volatile careers with periods of temporary work agency employment	x	x	x	8.90%	x	8.15%	11.20%	x	x	6.71%	4
*	Mostly temporary contracts, income <€2000	x	x	x	x	11.25%	6.31%	x	8.79%	x	x	3
*	Quick transition to permanent employment, income €1750	x	x	4.23%	x	x	x	x	5.05%	x	4.26%	3

Table 2.2: *(continued)*

		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6	Sample 7	Sample 8	Sample 9	Sample 10	Count
*	Mostly temporary contracts, income €3000+	x	x	x	x	x	x	3.31%	x	x	4.35%	2
*	Later transition to permanent employment, income €1500-€2000	x	x	x	3.93%	x	4.49%	x	x	x	x	2
*	Quick transition to permanent employment, income €2500-€3000	x	x	x	2.72%	x	x	x	x	7.56%	x	2
*	Quick transition to permanent employment, income <€1500	x	x	x	x	x	x	9.06%	x	x	x	1
*	Passing permanency, incomes €3000	x	x	x	x	3.09%	x	x	x	x	x	1
*	Volatile careers with periods of inactivity	x	x	x	6.59%	x	x	x	x	x	x	1
*	Mostly temporary contracts, income €2500+	x	x	x	x	x	4.86%	x	x	x	x	1

The aforementioned replication strategy was executed as follows. First, ten random non-overlapping 6.5% samples were drawn from the original population of 680,180 individuals. This was the largest sample size on which sequence analysis could be performed with the available computational power. This means that, in total, 442,882 individuals were included in the analysis. For each of these samples, cluster solutions up to 25 clusters were created. Previous explorative analyses indicated that this is the upper limit of the expected number of clusters. For each sample, every additional cluster was scrutinized based on whether it added substantive information to the typology, for instance by splitting up an existing cluster into two clusters with different career patterns or very different income levels. In terms of labour market positions, we valued substantive information about employment over information about non-employment. For example, a split between on-call workers and temporary work agency workers would be considered as substantive, whereas a split between late transitions to welfare and early transition to welfare would not be considered substantive. If an additional cluster did not add new substantive information to the typology, the cluster solution without that cluster was chosen as the optimal solution for that sample. The optimal cluster solutions for the ten samples were then compared, and the most frequent optimal number of clusters was determined. In our case, the optimal number of clusters turned out to be 17, which was the optimal solution in three of the ten samples. In other samples, the optimal number of clusters varied between 16 and 20 clusters.

Second, for the same ten samples, solutions with the optimal number of clusters (17) were created. With very heterogeneous sequences, it is unlikely that the outcomes of the 17-cluster solutions of the ten samples are identical. Therefore, the cluster solutions of the different samples were compared, and the occurrence of the various clusters was counted. Giving clusters short substantive descriptions, or *mottos*, simplified this process. The clustering solution of the first sample was consequently compared to the other samples. Every time a cluster was found to be substantively different from any of the clusters found in previous solutions, it was added to the list and was searched for in following sample solutions. The outcome of this process was a list of all the clusters that could be found in the population and the frequency in which these clusters occurred. In our data, 28 different clusters could be identified in the ten 17-cluster solutions. The final typology was then created by identifying the clusters that occur frequently, to make sure that their occurrence is not coincidental, and subsequently selecting a sample in which all these clusters were present. This ensures the reliability of the typology. In our data, 17 of the 28 clusters were present in at least five of the ten samples. Our final typology thus consists of 17 career types. Sample 1 contained all these most frequent clusters and can be regarded as the most representative sample for the full typology. The results of the replication strategy can be found in Table 2.2. The table shows the frequency of the clusters in the ten random samples and the sizes of the clusters in these samples. The lower part of the table furthermore displays which clusters were not included in the typology as they were only present in less than five of the samples. The resulting typology is discussed in the next section.

2.4. Results

The typology is graphically illustrated using sorted index plots (Scherer, 2001) that are created using the most representative sample (sample 1). These plots of all 17 clusters are presented in the appendix to this chapter . In these plots, the different states are denoted using different colours. The x-axis indicates the position, in this case the time in months, while every point in the y-direction indicates an individual. Each cluster in the typology is given a *motto* that describes the careers within that cluster. These mottos are presented in Table 2.3, together with the mean size of the cluster in the 10 samples of the replication strategy, and some descriptive statistics on the main demographic characteristics of the clusters.

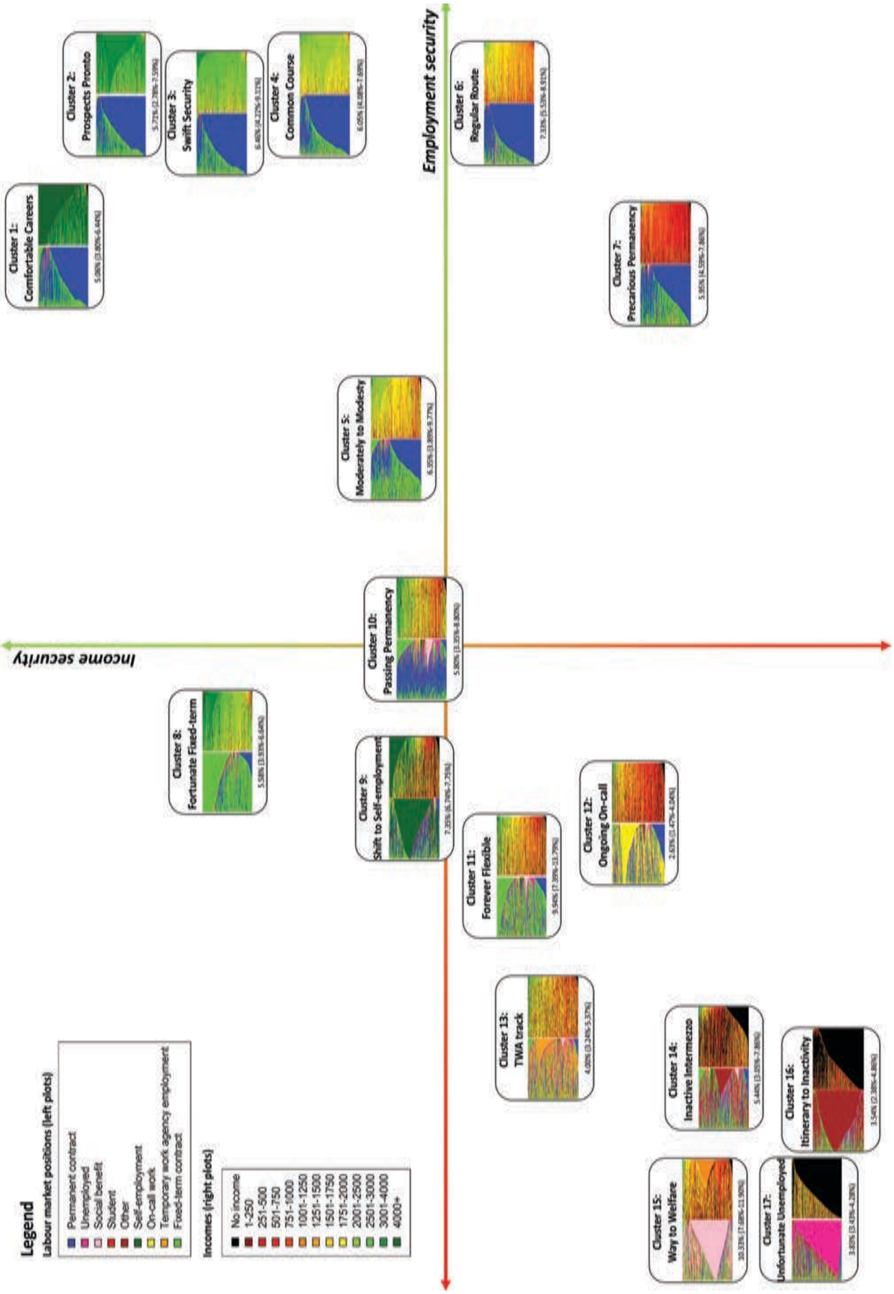
The two channels of the multichannel sequence analysis – labour market position and income – refer to two important aspects of employment-career quality: employment security and income security. Grouping trajectories in a typology with a meaningful number of clusters offers us the opportunity of distinguishing the prosperous from the precarious clusters in terms of these two types of security. Therefore, we position the clusters on a grid with two dimensions: employment security and income security. This grid is depicted in Figure 2.1. We use several indicators to assess the employment and income security of the careers. A discussion on the validity and the exact values of these indicative measures per cluster can be found in the appendix to this chapter. In this grid, employment security is indicated by 1) the mean percentage of individuals in the cluster that are employed throughout the observation period, 2) the mean duration until a transition to permanent employment in the cluster, based on Kaplan-Meier estimates, 3) the mean number of job changes that individuals in the cluster experience within the observation period, and 4) the contract types encountered in the cluster. For instance, a career in which workers make the transition from fixed-term employment to permanent employment and remain in permanent employment has more employment security than a career in which workers alternate frequently between different types of temporary employment or unemployment. Income security is indicated by 1) the mean average income earned by individuals in the cluster during their careers and 2) the mean standard deviation of income individuals earned during their careers.

Table 2.3: Cluster motto's and descriptive cluster characteristics

Cluster motto	N of most represen-tative sample	Mean size (%) over 10 samples[1]	Size (%) of most represen-tative sample	Gender		Level of education				Ethnicity			Mean (SD) age
				Male (%)	Female (%)	Educa-tion missing (%)	Low educa-tion (%)	Average educa-tion (%)	High educa-tion (%)	Native Dutch (%)	Western minority (%)	Non-western minority (%)	
Total sample	44571	101.4	100.0	48.1	51.9	43.4	29.0	43.1	22.9	72.8	10.3	16.9	36.0 (10.08)
1. Comfortable Careers	2860	5.1	6.4	77.0	23.0	35.4	2.2	21.5	76.4	84.1	10.2	5.7	37.9 (9.30)
2. Prospects Pronto	2566	5.7	5.8	69.1	30.9	39.8	7.0	32.9	60.1	83.5	9.3	7.2	36.2 (8.72)
3. Swift Security	2943	6.5	6.6	60.1	39.9	42.2	13.2	47.1	39.7	81.2	8.6	10.1	34.4 (9.19)
4. Common Course	1811	6.1	4.1	51.4	45.9	48.4	22.2	52.1	25.7	79.3	9.4	11.2	34.7 (9.69)
5. Moderately to Modesty	1995	6.4	4.5	41.2	58.8	40.3	30.1	50.9	19.0	77.8	10.1	12.0	33.9 (9.31)
6. Regular Route	3445	7.3	7.7	21.0	79.0	49.8	29.6	50.3	20.1	79.6	8.5	11.9	36.9 (9.89)
7. Precarious Permanency	2362	6.0	5.3	11.6	88.4	53.9	42.1	45.8	12.1	79.2	8.5	12.4	39.5 (9.55)
8. Fortunate Fixed-term	1742	5.6	3.9	70.2	29.8	39.4	13.9	43.0	43.0	82.5	9.5	8.0	34.2 (9.04)
9. Shift to Self-employment	3196	7.4	7.2	55.3	44.7	44.0	21.2	41.8	37.0	74.3	9.7	16.0	36.4 (9.48)
10. Passing Permanency	2199	5.8	4.9	49.3	50.7	41.5	23.0	48.1	28.8	77.1	9.6	13.2	35.8 (9.83)
11. Forever Flexible	5158	9.9	11.6	42.2	57.8	37.6	31.6	50.1	18.3	74.4	9.5	16.1	35.3 (10.26)
12. Ongoing On-call	1447	2.6	3.9	24.7	75.3	51.9	38.8	48.3	12.9	76.8	9.2	14.0	37.9 (10.99)
13. Temporary Work Agency Track	1617	4.0	3.6	66.1	33.9	38.2	38.7	51.1	10.2	63.6	11.1	25.4	34.6 (10.30)
14. Inactive Intermezzo	2791	5.4	6.3	37.2	62.8	42.0	40.2	43.8	16.0	62.2	12.6	25.3	33.2 (10.72)
15. Way to Welfare	5281	10.3	11.9	55.0	45.0	42.0	55.4	36.9	7.7	56.7	10.3	33.0	36.7 (10.81)
16. Itinerary to Inactivity	1488	3.5	3.3	21.4	78.6	54.4	43.4	39.8	16.8	65.5	11.4	23.1	39.1 (11.11)
17. Unfortunate Unemployed	1670	3.8	3.8	57.4	42.6	53.0	33.5	39.4	27.1	42.6	23.1	34.3	36.0 (10.56)

[1] Because we look at the mean sizes of the clusters of the 10 samples, the total size does not add up to 100%.

Figure 2.1: The 17 clusters of employment careers located on a grid of employment security and income security



In every cluster that appears in the grid, sequences of labour market positions are always placed in the left plot, while income sequences are displayed in the right plot. In what follows, we discuss the typology per quadrant of the grid of Figure 2.1. We also briefly discuss some of the demographic characteristics of the clusters in the quadrants. As these figures are only based on descriptive statistics, we defer from making any causal inference. For more detailed information on the clusters, we refer to the appendix to this chapter.

In the top right quadrant of the grid, we find the careers that are characterized by high levels of both employment security and income security. Individuals in these clusters make the transition to permanent employment on average after around 17 to 22 months, which is in most cases the final transition within the observation period. Only the cluster *Moderately to Modesty* deviates from this pattern as, in this cluster, it takes workers in this cluster approximately three years to enter permanent employment. Contrary to labour market positions and contract types, incomes in this quadrant vary somehow between clusters. Individuals in *Comfortable Careers* are the most well-off, as most of them earn monthly wages of at least €4000, followed by individuals in *Prospects Pronto*, whose wages grow to around €3000 within the observation period. In this quadrant, the wages are lowest – around €1700 – in *Moderately to Modesty*. However, incomes in this cluster tend to increase over time. Overall, this quadrant consists of career types of individuals who fare well since temporary employment functioned as a stepping stone for them. In total, 29.6% of the individuals are in clusters that mainly consist of stepping stone careers. Descriptive statistics of the clusters in this quadrant show that higher educated native Dutch men tend to be overrepresented in this quadrant, especially in clusters with higher income levels. For example, in the cluster of *Comfortable Careers*, 77% are male and 76.4% are higher educated.

The bottom right quadrant of the grid includes the clusters that are characterized by high employment security but low income security, that together contain 13.3% of the total sample: *Regular Route* and *Precarious Permanency*. Individuals in *Precarious Permanency* make the transition to permanent employment after around two years, just like the individuals in the top right quadrant. However, these individuals earn wages of around €750 monthly on average. In *Regular Route*, individuals make the transition to permanent employment after around 17 months on average. The incomes in this cluster are quite heterogeneous, but on average individuals earn a modest €1500, while only few earn more than €2000 monthly. Previous research would have classified the careers in these clusters as stepping stones based on their employment security. However, the low income security in this quadrant makes these careers much more precarious and deter us from classifying them as stepping stones. Descriptive statistics indicate that women are highly overrepresented in this quadrant (79% in *Regular Route* and 88.4% in *Precarious Permanency*). Furthermore, lower educated individuals are overrepresented in *Precarious Permanency* (42.1%). This cluster also has the highest average age (39.5 years). The overrepresentation of women in this quadrant is due to the fact that a large share of women in the Netherlands works part-time, which has as a consequence that they have lower monthly incomes. In many cases, these women can also rely on their partner's income. The actual precarity of these individuals may thus be overestimated. However, with such incomes, these individuals are not economically independent. In the case that the partner's income is discontinued for whatever reason, the individual remains in a precarious situation.

In the bottom left quadrant we find the clusters with careers that have both relatively low employment security and low income security. These careers would fit the classical trap image as it consists of the more precarious groups in the labour market, which sum up to 39.7% of the individuals. Such careers are very common in the clusters *Way to Welfare* and *Unfortunate Unemployed,* that consist of careers characterized by transitions to welfare benefits or unemployment respectively, and in *Itinerary to Inactivity* and *Inactive Intermezzo*, in which individuals permanently or temporarily leave the labour market either. Descriptive statistics show that women are overrepresented in *Itinerary to Inactivity* (78.6%) and *Inactive Intermezzo* (62.8%), while men are overrepresented in *Way to Welfare* (55.0%) and *Unfortunate Unemployed* (57.4%). For all four clusters holds that native Dutch individuals are underrepresented (especially in *Unfortunate Unemployed,* where 57.4% of the individuals are non-Dutch) while lower educated individuals are overrepresented. *Unfortunate Unemployed* however also has a relatively high share of higher educated individuals (27.1%). Interestingly, individuals in *Itinerary to Inactivity* are on average quite old (mean age 39.1) while individuals in *Inactive Intermezzo* are on average youngest of all clusters (mean age 33.2).

Nevertheless, in the same quadrant, we also find careers in which individuals mostly are employed, but still lack both income and employment security. Individuals in the clusters *On-going On-call* and *Temporary Work Agency Track* have careers that consist mostly of the type of temporary employment that is indicated in the cluster mottos, which in general offer less security than fixed-term contracts. Unsurprisingly, most careers in the *Temporary Work Agency Track* are characterized by frequent job changes and a relatively low percentage of time spent in employment. This is also the case, but to a lesser extent, for the cluster *Ongoing On-call*, which indicates that the individuals in this cluster have more employment security than the individuals in the *Temporary Work Agency Track*. Furthermore, wages in these two clusters are relatively low and rarely exceed €1500 monthly - with the exception of a few individuals in the *Temporary Work Agency Track*. Also, given the frequent changes within income sequences and the relatively high standard deviations of individuals' incomes (see the appendix to this chapter), incomes in these clusters fluctuate more than in the other quadrants. This is a clear indication of low income security. Descriptive statistics indicate that lower educated individuals are overrepresented in both these clusters (38.8% in *Ongoing On-call* and 38.7% in *Temporary Work Agency Track*). In *Ongoing On-call*, native Dutch and women are overrepresented (76.8% and 75.3%, respectively), while in the *Temporary Work Agency Track*, most of the individuals are male and relatively many have a non-western migration background (66.1% and 25.4%, respectively).

This bottom left quadrant further contains the cluster *Forever Flexible* with careers where individuals remain in fixed-term employment for most of the observation period. The individuals in this cluster have relatively stable careers in fixed-term jobs, which make them score higher in employment security compared to the individuals in the *Temporary Work Agency Track,* but they spend less time in employment than workers in *Ongoing On-call*. Their wages are generally low, approximately €1500 monthly on average. Descriptive statistics show that a small majority of the individuals in this cluster is female (57.8%) and that there are relatively more individuals than average with an average level of education (50.1%).

Nonetheless, not all individuals who have careers that consist mostly of fixed-term employment should be called precarious. The cluster *Fortunate Fixed-term*, that contains 5.6% of the sample, is situated in the upper left quadrant of the grid as it mostly contains sequences with a lengthy stay in fixed-term jobs, but also high (between €2000 to more than €4000) and increasing wages. Some individuals of this cluster enter permanent employment after some time, but return to fixed-term employment later on. Such relapses are mostly not accompanied by income decreases, which probably indicates that these transitions are voluntary. Thus, though these careers would fit the traditional trap-image of repeated temporary jobs, the high incomes in this cluster allow these careers to be labelled prosperous, rather than precarious. 70.2% of the individuals in this cluster are male and 43% are higher educated. Native Dutch individuals are furthermore overrepresented in this cluster (82.5%).

On the x-axis between the upper and lower left quadrants, we also find a cluster that mostly contains careers that lead to self-employment, *Shift to Self-employment,* that contains 7.4% of the sample. In general, self-employment scores lower on employment security than regular fixed-term employment or permanent employment, as future employment depends solely on the efforts of the self-employed to find new clients. The incomes in this cluster also vary considerably: there are some self-employed individuals who see their incomes increase to over €4000 monthly, whereas also many individuals earn very low incomes. Therefore, this cluster is placed on the border of the two quadrants, as some fare well, but others are stuck in precarity. Descriptive statistics show that this cluster contains slightly more men than women (55.3%) and relatively many higher educated individuals (37%).

Finally, there is one cluster that holds a middle position in the grid: *Passing Permanency*. This group represents 5.8% of the sample. Careers in this cluster are characterized by a high level of heterogeneity in both labour market position and income. Employment sequences are very volatile and usually include a return to fixed-term employment. Individuals mostly start in fixed-term employment and enter permanent employment after around one year. For this reason, previous research would have classified these careers as stepping stones. However, after around four years in permanent employment, a large share of the individuals returns to fixed-term employment, either directly or through a period of unemployment. For some, this fixed-term job is followed by a new permanent job, for some by unemployment, while for others fixed-term employment persists. Incomes in this cluster are quite heterogeneous. Many individuals see their income increasing throughout the observation period, while others experience income decreases. This cluster clearly shows that permanent employment is not necessarily the final outcome of a career, and that the quality of the career should not be determined based upon that one specific transition (i.e. to permanent employment). According to descriptive statistics, individuals in this cluster are slightly higher educated than average (28.8%), but the gender distribution is almost perfectly balanced.

The typology shows that there is considerable variation in temporary employment careers. We can conclude that 29.6% of the workers as a typical stepping stone career while 39.7% has a career that can be classified as a trap. Most important however is the fact that not all careers fit in the original stepping stone and trap dichotomy. 13.3% of the individuals combine high employment security with low income security, making their careers, which would usually be classified as successful, much more precarious. 5.6% of the individuals combine low employment security with high income security, making their careers that would usually be classified as traps much less precarious. Finally, 5.8% have careers in which the permanent job did not turn out to be the final outcome, making their careers, which would usually be classified as stepping stones, much less stable. Combined, these groups make up 24.7% of the sample. This means that almost a quarter of careers would have been misclassified in previous research.

2.5. Conclusion and discussion

The aim of this chapter was to provide a detailed picture of employment and income careers using a holistic approach. For this purpose, a multichannel sequence analysis with labour market position and income as factors was used to study the careers of individuals in the Netherlands who started a job with a temporary employment contract in 2007. The multichannel sequence analysis was complemented by a replication strategy to ensure the reliability of the results. This analysis resulted in a typology of 17 types of temporary employment careers that partly deviate from the 'traditional' division between stepping stone and trap careers that is dominant in previous literature.

Three important conclusions can be drawn from this analysis. The first is that a career that involves working with a temporary employment contract is not always precarious, as is often assumed by labour market segmentation theories. Actually, the type of temporary employment is crucial in determining whether the career is precarious or not. Working for temporary employment agencies or on an on-call contract leads to low levels of both career and income security. In contrast, working with a fixed-term contract may lead to several outcomes: either low or high employment security combined with again low or high income security.

The second conclusion is that employment with a permanent contract is not necessarily a good nor a final outcome, as previous research suggests. Many individuals who enter permanent employment relatively quickly still earn relatively low wages (13.3% of the sample). The same low wages are also observed for other individuals that have to wait long before they can enter permanent employment. These findings make it questionable whether the permanency of the job can uniformly define a good career outcome. Furthermore, for a fair amount of individuals (5.8% of the sample), employment with a permanent contract is not the final outcome in their career as they return to temporary employment. For some, this seems to be a voluntary choice, as this transition is accompanied by wage increases. For others this transition is most probably involuntary as it is accompanied by a period of unemployment.

The last and most important conclusion of this chapter is that making the distinction between traps and stepping stones only does not fully render justice to the large variety in temporary employment trajectories that is observed in the Dutch labour market: although 29.6% of the careers can be classified as stepping stones and 39.7% as traps, about a quarter (24.7%) of the individuals follow a career that does not fit into the original trap and stepping stone scenarios, because they combine high income security with low employment security or vice versa, or because the permanent contract was not the final outcome in the career. This diversity should be taken into account when studying temporary employment and its outcomes and when formulating policies, as these groups are otherwise neglected. For policy makers, it could be an option to change the focus from specific policies that aim at improving the position of workers holding particular contract types to policies that strive to improve the working conditions of the all the more precarious individuals, regardless of their contract type.

This chapter corroborates the claim of recent previous research – most importantly Fuller and Stecy-Hildebrandt (2015) – that a holistic approach such as sequence analysis gives more detailed insights into the labour market than an analysis of point-in-time transitions. Analysing employment careers with sequence analysis allows us to study the quality of employment careers by studying several aspects of job quality simultaneously (here: labour market positions and income), and to take into account the considerable heterogeneity of the types of temporary employment, while it does not assume permanent employment to be the only good outcome.

This chapter contributes as well to our overall understanding of the role of temporary employment in shaping social inequality. Segmentation theorists often see temporary employment as a source of inequality and typically proxy the secondary segment of the labour market by employment with temporary contracts. Our analysis shows that reality in the labour market is much more complex than the division between jobs with permanent contracts in a specific firm and with fixed working hours and jobs with fixed-term contract and/or variable hours in different firms. Except for the obvious inequality that exists between different income levels and that can be clearly attributed to some employment contract types, such as temporary agency contracts and on-call contracts, there is a lot more inequality to explain within careers with fixed-term contracts.

Though we have shown that sequence analysis is a useful tool for understanding labour market inequalities, this study also suffers from some limitations. The first is that we make statements about the quality of careers based on labour market positions and incomes only. Though we clearly go a step further than most previous research, subjective aspects of job quality, such as job satisfaction, should be taken into account as well (Kalleberg, 2011). Register data such as we used for this study are unable to capture these aspects. Second, we can only draw conclusions about the specific subgroup of persons who have entered temporary employment in 2007. We cannot make any claims about the extent to which the trajectories of this group differ from the trajectories of individuals who have never entered temporary employment. Finally, we are limited in our possibility to draw conclusions about the self-employed, both because we have limited information about their incomes, making it likely that their incomes are underestimated, and because we do not distinguish cases where individuals combine self-employment with dependent employment.

Explaining inequality in the labour market is the step that naturally follows from this chapter. The career clusters may vary in their composition according to demographic or human capital factors such as gender, education, occupation and training opportunities. In our register data, there was only limited information available about the background characteristics of individuals. Linking register data with survey data, which is an increasingly used practice of Statistical Offices, may provide more detailed data on background characteristics is available. These data allow for a detailed causal analysis and can be a fruitful source for further research.

Appendix to chapter 2: Descriptive statistics per cluster

In this appendix, descriptive statistics of the total sample and the 17 cluster solutions will be discussed. Concerning the size of the clusters, we will depict the mean size of the cluster over the 10 samples of the replication strategy and the size of the cluster in the most representative sample (sample 1). All other statistics describe the most representative sample, which is also used for the creation of the sorted index plots.

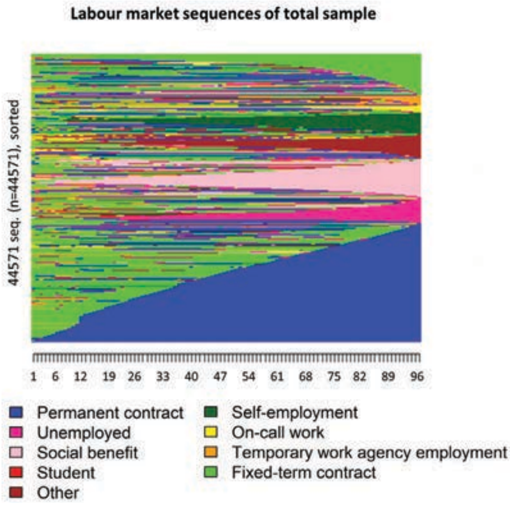
As general descriptive statistics, we include gender, ethnicity, age and level of education. As level of education has only been structurally registered in recent years, the level of education is not available for over 40% of the sample. These missing values are thus not random, but linked to age, as level of education has not been registered structurally for older individuals. For some older individuals, the level of education is available. These data are retrieved from participants in the Dutch Labour Force Survey.

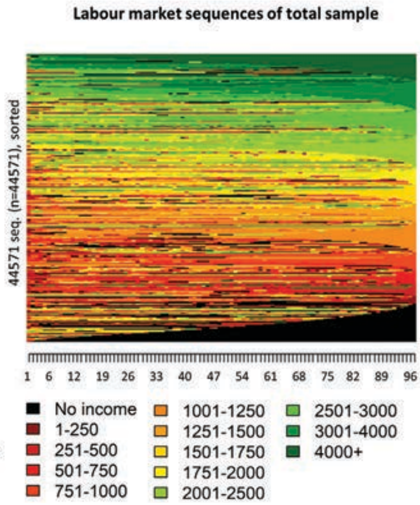
As indicators of employment security, we take into account several indicators. First, we look at the percentage of time an individual spent in employment during the career. Second, we look at the number of employer changes the individual experiences during the career. This measure however is not fully reliable as we do not have employer information, but rather a job identifier. If someone for instance makes a promotion to another position within the same firm, the job identifier may change as well. This is unfortunately not the employer change we intend to measure. Furthermore, the actual employers of individuals who are in temporary work agency employment is not known, as only the temporary work agency is known. When the temporary work agency worker changes employers while working for the same temporary work agency, this is not registered. Therefore, this measure should not be used as an absolute measure of the number of employer changes that occur within the cluster, but rather as an indicator that can be used to compare the clusters' volatility. Finally, we look at the mean duration until an individual enters permanent employment, based on Kaplan-Meier estimates. This duration is measured in months.

Indicators of incomes security are the mean income an individual earns during the career and the standard deviation of the income the individuals earn during the career. This standard deviation indicates the stability of the income.

Finally, we include two more general sequence measures: discrepancy and turbulence. Discrepancy is a measure of the heterogeneity of the sequences within one cluster. The higher the discrepancy, the more heterogeneous the careers are. The discrepancy scores of the clusters cannot be compared to the discrepancy of the total sample, as the presence of all sequences in the total sample leads to the highest discrepancy score. Turbulence is a measure of the volatility of the sequences: the more transitions are made within the career sequences, both in terms of labour market position and income, the more turbulent a career is. The turbulence of the clusters can be compared to the mean turbulence of the total sample to determine whether a cluster is more or less volatile.

Total Sample





Characteristics	
N of current sample	44571
Mean % of 10 samples	101.4%
% of current sample	100%
Male	48.1%
Female	51.9%
Education missing	43.4%
Low education	29.0%
Average education	43.1%
High education	22.9%
Native Dutch	72.8%
Western background	10.3%
Non-western background	16.9%
Mean(SD) age	36.0 (10.08)
Mean(SD) % time in employment	75.7 (31.25)
Mean(SD) number of employer changes	3.5 (2.05)
Mean(SE) duration until permanent employment	43.2 (0.18)
Mean(SD) income (€)	1871 (1397)
SD(SD) income (€)	580 (939)
Discrepancy	160.2
Turbulence	8.80

Description

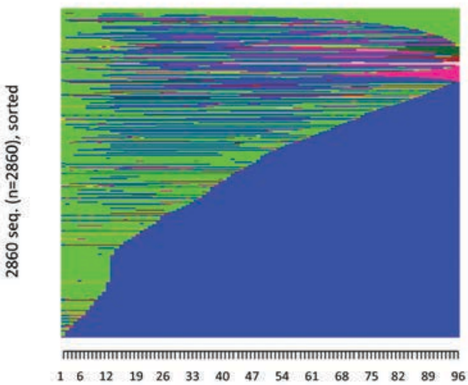
This sample consists of 44571 individuals who entered temporary employment in 2007. 41% of the individuals end the observation period in permanent employment, but it is certainly not the only outcome individuals experience. All income levels are represented in the sample. The discrepancy of 160.2 indicates that the sample is very heterogeneous. The turbulence of 8.80 indicates that also within careers, there are quite some changes, making the careers quite volatile.

On average, individuals spend 75.7% of their career in employment and change employers on average 3.5 times. Furthermore, it takes 43 months on average for individuals to enter permanent employment for the first time.

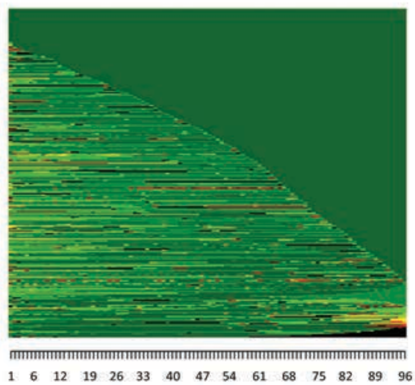
The incomes earned by the workers are around €1900 monthly and fluctuate on average with €580 during the career.

Cluster 1: Comfortable Careers

Cluster 1 Labour market position sequences

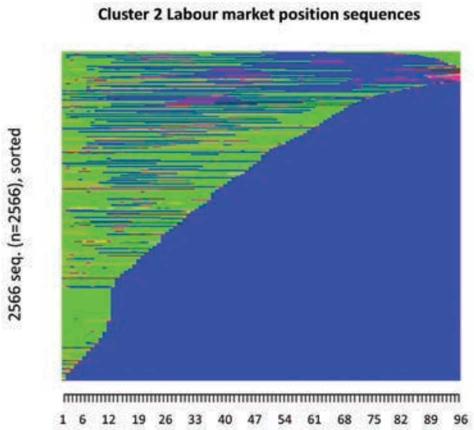


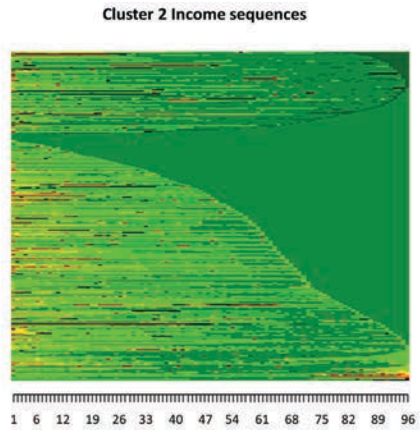
Cluster 1 Income sequences



Characteristics		Description
N of current sample	2860	The careers in this cluster are characterized by quick transitions from fixed-term to permanent employment. For some these last for the rest of the observation period, while others return to fixed-employment again, some entering permanent employment a bit later on again. Individuals spend around 96% in employment throughout their careers and change employers on average 3.6 times. These individuals thus have quite a lot of employment security. The incomes earned in this cluster are very high, with individuals earning €4700 monthly on average throughout their careers. The high standard deviation of career income most likely indicates the income increase throughout the career. This clusters thus scores high both in terms of employment security as well as in terms of income security.
Mean % of 10 samples	5.06%	
% of current sample	6.42%	
Male	77.0%	
Female	23.0%	
Education missing	35.4%	
Low education	2.2%	
Average education	21.5%	
High education	76.4%	
Native Dutch	84.1%	
Western background	10.2%	
Non-western background	5.7%	
Mean(SD) age	37.9 (9.3)	
Mean(SD) % time in employment	95.8 (9.30)	
Mean(SD) number of employer changes	3.6 (1.55)	
Mean(SE) duration until permanent employment	22.8 (0.43)	
Mean(SD) income (€)	4719 (1721)	
SD(SD) income (€)	1010 (1339)	
Discrepancy	84.9	
Turbulence	5.70	

Cluster 2: Prospects Pronto





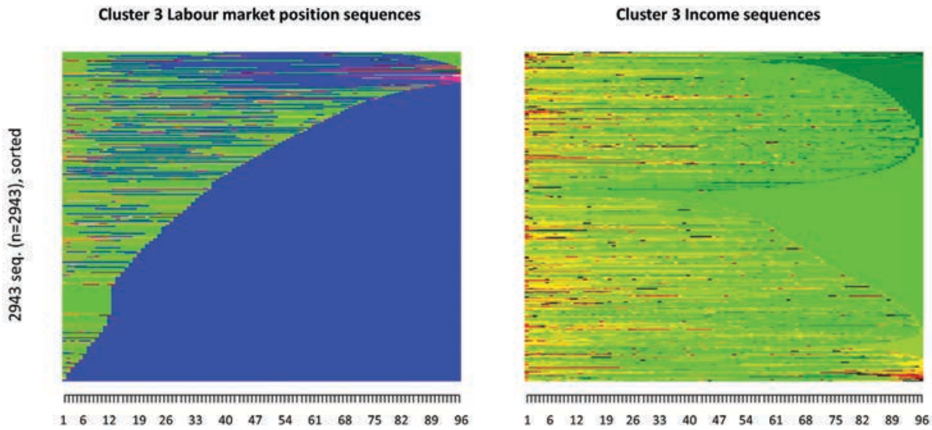
Characteristics	
N of current sample	2566
Mean % of 10 samples	5.71%
% of current sample	5.76%
Male	69.1%
Female	30.9%
Education missing	39.8%
Low education	7.0%
Average education	32.9%
High education	60.1%
Native Dutch	83.5%
Western background	9.3%
Non-western background	7.2%
Mean(SD) age	36.2 (8.72)
Mean(SD) % time in employment	97.8 (5.29)
Mean(SD) number of employer changes	3.5 (1.42)
Mean(SE) duration until permanent employment	21.3 (0.355)
Mean(SD) income (€)	3112 (332)
SD(SD) income (€)	479 (297)
Discrepancy	75.6
Turbulence	5.50

Description

In this cluster, individuals start their career in fixed-term employment. Many individuals make the transition to permanent employment quite quickly. For some, this permanent employment lasts until the end of the observation period. Others return to fixed-term employment which is in most cases again followed by permanent employment. These individuals spend most of their careers in employment and change employers on average 3.5 times, giving these individuals a lot of employment security.

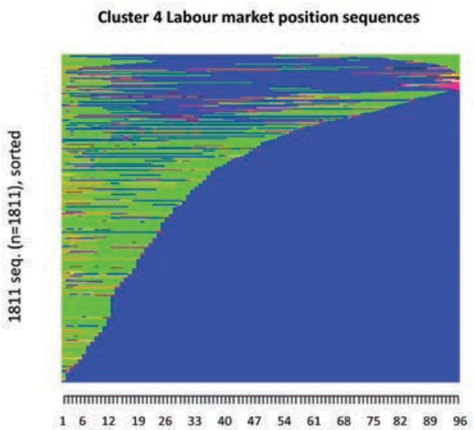
The incomes in this cluster are relatively high, with individuals earning €3100 monthly on average throughout their careers. Most individuals experience an income increase during their careers, which is reflected in the relatively high standard deviation. The income security in this cluster is thus quite high as well.

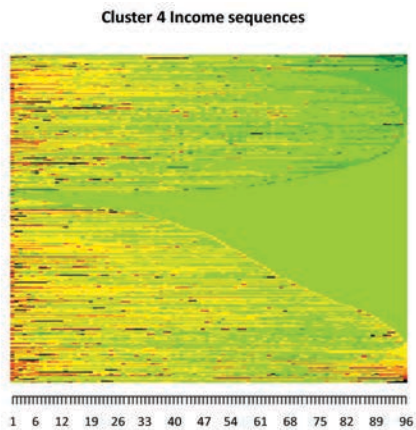
Cluster 3: Swift Security



Characteristics		Description
N of current sample	2943	Individuals in this cluster start their careers mostly in fixed-term employment or temporary work agency employment and make the transition to lasting permanent employment on average after around two years. Before that transition occurs, many individuals also experience shorter spells of temporary work agency employment or permanent employment, which lowers the mean duration until permanent employment. Individuals spend almost their entire career in employment and change employers 3.5 times on average. These individuals thus have high employment security. Individuals in this cluster experience a wage increase throughout their careers, earning at least €2500 or more at the end of the observation period. With a standard deviation of €400 that is most likely explained by this income increase, these incomes are rather stable, giving these individuals a lot of income security as well. Overall, these careers are quite stable, with a turbulence of 5.33, and also relatively homogeneous, as the discrepancy level of 85.5 is one of the lowest of all clusters.
Mean % of 10 samples	6.46%	
% of current sample	6.60%	
Male	60.1%	
Female	39.9%	
Education missing	42.2%	
Low education	13.2%	
Average education	47.1%	
High education	39.7%	
Native Dutch	81.2%	
Western background	8.6%	
Non-western background	10.1%	
Mean(SD) age	34.4 (9.19)	
Mean(SD) % time in employment	98.1 (4.64)	
Mean(SD) number of employer changes	3.5 (1.47)	
Mean(SE) duration until permanent employment	20.9 (0.33)	
Mean(SD) income (€)	2479 (243)	
SD(SD) income (€)	415 (250)	
Discrepancy	85.5	
Turbulence	5.33	

Cluster 4: Common Course





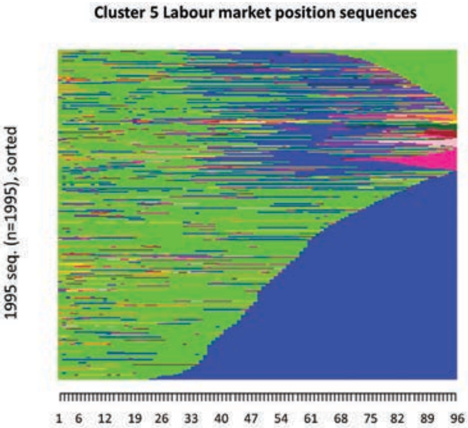
Characteristics	
N of current sample	1811
Mean % of 10 samples	6.05%
% of current sample	4.06%
Male	51.4%
Female	45.9%
Education missing	48.4%
Low education	22.2%
Average education	52.1%
High education	25.7%
Native Dutch	79.3%
Western background	9.4%
Non-western background	11.2%
Mean(SD) age	34.7 (9.69)
Mean(SD) % time in employment	98.4 (3.60)
Mean(SD) number of employer changes	3.4 (1.37)
Mean(SE) duration until permanent employment	17.3 (0.304)
Mean(SD) income (€)	2081 (172)
SD(SD) income (€)	319 (172)
Discrepancy	75.5
Turbulence	5.27

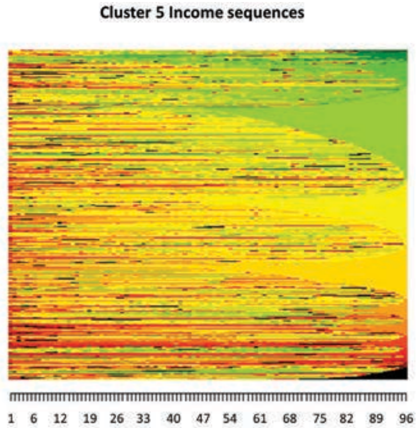
Description

In this cluster, individuals make the transition from fixed-term employment to mostly lasting permanent employment on average within two years. Some individuals however experience shorter spells of permanent and other types of employment before that transition. The individuals in this cluster spend almost their entire career in employment and change employers on average 3.4 times, giving these careers a lot of employment security.

In these jobs, the incomes are quite stable: during the careers the incomes fluctuate with around €300. This can be partially explained by the fact that the incomes in this cluster generally increase over time. At the end of the observation period, most individuals earn at least €2000 monthly or more. This cluster thus has quite high employment security and high income security.

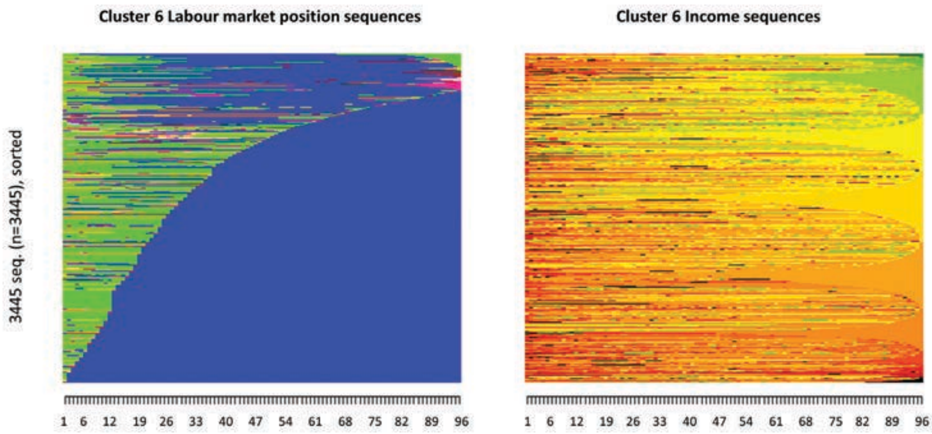
Cluster 5: Moderately to Modesty





Characteristics		Description
N of current sample	1995	The careers in this cluster are characterized by transitions from fixed-term employment to permanent employment, that occur after around 39 months on average. In many cases, individuals experience several labour market transitions before entering permanent employment. For almost two thirds of the individuals, the permanent job lasts for the rest of the observation period. Most of the others return to fixed-term employment, and a few become unemployed. These individuals also spend most of their careers in employment and change employers 4.4 times on average. The incomes earned in this career are not low, with individuals earning around €1700 monthly on average. These incomes fluctuate throughout the careers on average with almost €400. Compared to other stepping stone clusters with higher average incomes, this cluster is relatively heterogeneous and much more volatile, indicating that the individuals in this cluster experience both less employment security and income security than the individuals in those other clusters. However, we do not consider the levels of employment security and income security to be low enough to classify these individuals as precarious.
Mean % of 10 samples	6.35%	
% of current sample	4.48%	
Male	41.2%	
Female	58.8%	
Education missing	40.3%	
Low education	30.1%	
Average education	50.9%	
High education	19.0%	
Native Dutch	77.8%	
Western background	10.1%	
Non-western background	12.0%	
Mean(SD) age	33.9 (9.31)	
Mean(SD) % time in employment	93.7 (5.48)	
Mean(SD) number of employer changes	4.4 (1.94)	
Mean(SE) duration until permanent employment	39.2 (0.48)	
Mean(SD) income (€)	1695 (390)	
SD(SD) income (€)	387 (205)	
Discrepancy	123.2	
Turbulence	9.02	

Cluster 6: Regular Route



Characteristics	
N of current sample	3445
Mean % of 10 samples	7.33%
% of current sample	7.73%
Male	21.0%
Female	79.0%
Education missing	49.8%
Low education	29.6%
Average education	50.3%
High education	20.1%
Native Dutch	79.6%
Western background	8.5%
Non-western background	11.9%
Mean(SD) age	36.9 (9.89)
Mean(SD) % time in employment	97.4 (5.48)
Mean(SD) number of employer changes	3.4 (1.55)
Mean(SE) duration until permanent employment	17.6 (0.24)
Mean(SD) income (€)	1453 (318)
SD(SD) income (€)	317 (238)
Discrepancy	104.8
Turbulence	5.42

Description

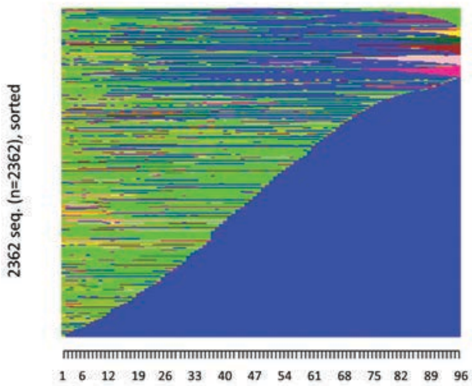
This cluster is characterized by careers in which most individuals spend the beginning of their careers in fixed-term employment, sometimes alternated with other labour market positions such as permanent employment that last for a shorter period of time. After 18 months on average, the transition to permanent employment is made. This permanent employment lasts for most individuals. Individuals spend 97.4% of their time in employment and change employers 3.4 times on average. These individuals thus have relatively high employment security.

During the careers, individuals earn on average around €1450 monthly. These incomes fluctuate during the careers with a standard deviation of €300.

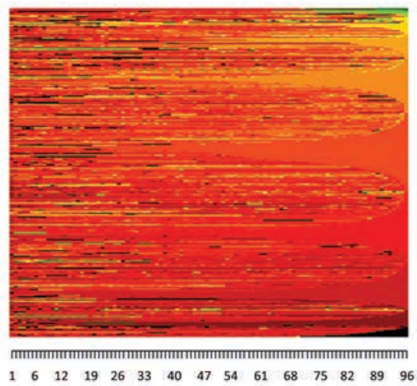
In general, the careers are relatively stable, given the low turbulence of 5.42. The careers in this cluster are however quite heterogeneous with a discrepancy of 104.8, especially when compared to other stepping stone clusters with higher average incomes.

Cluster 7: Precarious Permanency

Cluster 7 Labour market position sequences

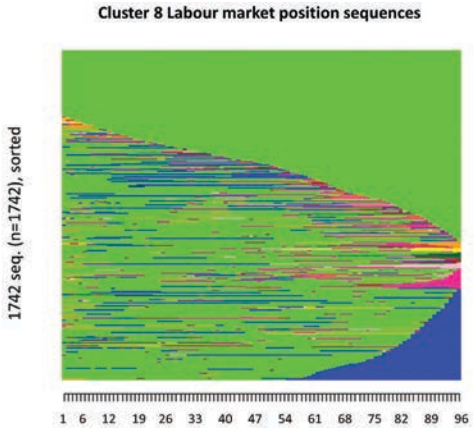


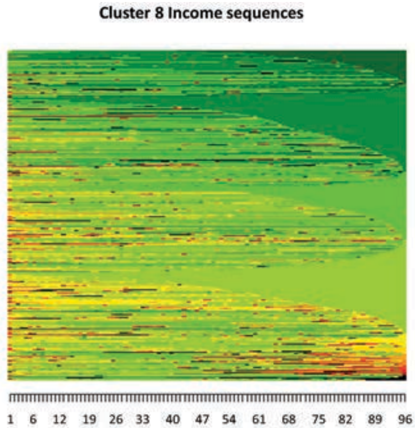
Cluster 7 Income sequences



Characteristics		Description
N of current sample	2362	In this cluster, individuals start their career in fixed-term employment, making the transition to permanent employment after around 27 months on average. Spending 94% of their time in employment and changing employers around 3.9 times, these individuals have quite some employment security. However, they lack income security: they earn only around €750 monthly, and these incomes fluctuate during the with around €250, which is quite a lot for such low incomes. Even though these individuals are employed in a permanent contract in the end, these careers can still be classified as precarious in terms of income security.
Mean % of 10 samples	5.95%	
% of current sample	5.30%	
Male	11.6%	
Female	88.4%	
Education missing	53.9%	
Low education	42.1%	
Average education	45.8%	
High education	12.1%	
Native Dutch	79.2%	
Western background	8.5%	
Non-western background	12.4%	
Mean(SD) age	39.5 (9.55)	
Mean(SD) % time in employment	94.2 (9.10)	
Mean(SD) number of employer changes	3.9 (1.91)	
Mean(SE) duration until permanent employment	26.9 (0.43)	
Mean(SD) income (€)	763 (310)	
SD(SD) income (€)	263 (311)	
Discrepancy	118.6	
Turbulence	7.96	

Cluster 8: Fortunate Fixed-term





Characteristics	
N of current sample	1742
Mean % of 10 samples	5.58%
% of current sample	3.93%
Male	70.2%
Female	29.8%
Education missing	39.4%
Low education	13.9%
Average education	43.0%
High education	43.0%
Native Dutch	82.5%
Western background	9.5%
Non-western background	8.0%
Mean(SD) age	34.2 (9.04)
Mean(SD) % time in employment	95.5 (9.19)
Mean(SD) number of employer changes	4.2 (1.95)
Mean(SE) duration until permanent employment	66.1 (0.866)
Mean(SD) income (€)	2575 (566)
SD(SD) income (€)	484 (366)
Discrepancy	103.3
Turbulence	5.98

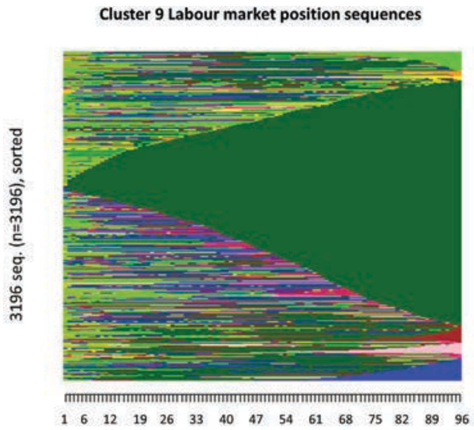
Description

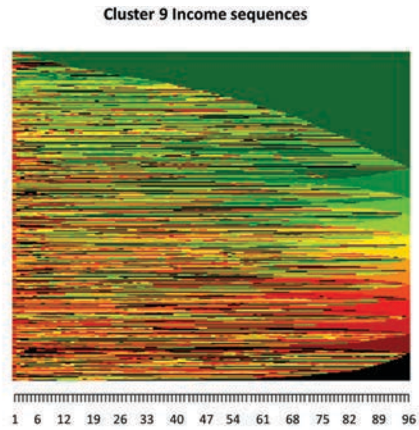
The individuals in this cluster have careers that mostly consist of fixed-term contracts. Some individuals enter permanent employment at some point of their career, after which some return to fixed-term employment. These individuals spend most of their career in employment, and change employers around 4.2 times. Even though these individuals spend most of their careers in temporary employment, they have more employment security than the individuals in cluster 8.

During their careers, the individuals earn on average around €2600 monthly, with a standard deviation of around €500. This relatively high standard deviation is in this cluster most likely due to the wage increases that most individuals in this cluster experience. The income security in this cluster is this quite high. Also in general, the careers in this cluster are quite stable, given the relatively low turbulence of 5.98.

Even though the labour market positions of the individuals in this cluster would normally classify these workers as precarious, the income security these workers have compensates for this, making it quite difficult to call this group precarious.

Cluster 9: Shift to Self-employment





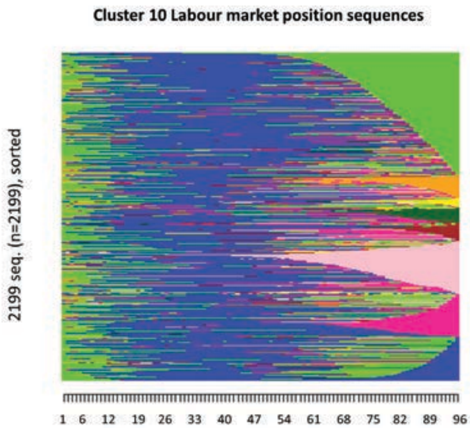
Characteristics	
N of current sample	3196
Mean % of 10 samples	7.35%
% of current sample	7.17%
Male	55.3%
Female	44.7%
Education missing	44.0%
Low education	21.2%
Average education	41.8%
High education	37.0%
Native Dutch	74.3%
Western background	9.7%
Non-western background	16.0%
Mean(SD) age	36.4 (9.48)
Mean(SD) % time in employment	89.2 (14.86)
Mean(SD) number of employer changes	2.2 (1.70)
Mean(SE) duration until permanent employment	57.1 (0.74)
Mean(SD) income (€)	2475 (2457)
SD(SD) income (€)	1684 (2505)
Discrepancy	136.1
Turbulence	8.86

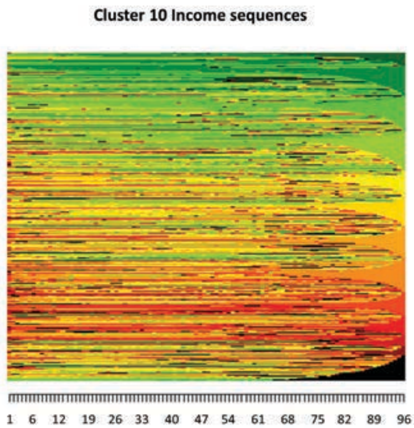
Description

This cluster depicts the careers of individuals who enter self-employment at some point in their career. In this cluster, individuals spend 89% of their career in employment and change employers 2.2 times on average. This indicator however does not include changing to self-employment. As self-employed individuals have to actively keep their business alive, their labour market position in general is more insecure than other types of dependent employment. The employment security of these workers is therefore on the lower side.

This cluster is very diverse, which is indicated by the high level of discrepancy in the cluster. This is mostly reflected in the income distribution of the individuals in this cluster: there are quite a lot of individuals who earn very high incomes whereas other individuals in this cluster earn less than €1000 monthly. This large income variation is also reflected in its large standard deviation. The incomes of these individuals also tend to fluctuate during the career, though the high standard deviation is likely due to the very high incomes in this cluster as well. This mix of successful and less successful self-employed individuals places this cluster in the middle of the income security axis of the cluster grid.

Cluster 10: Passing Permanency





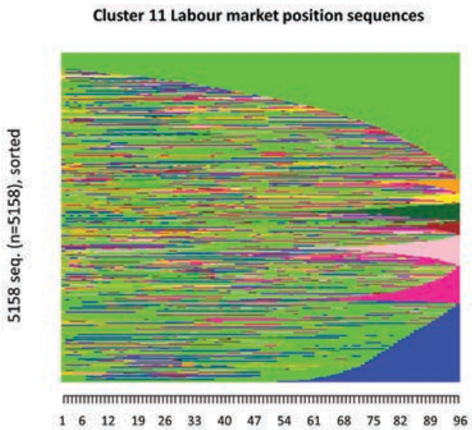
Characteristics	
N of current sample	2199
Mean % of 10 samples	5.80%
% of current sample	4.93%
Male	49.3%
Female	50.7%
Education missing	41.5%
Low education	23.0%
Average education	48.1%
High education	28.8%
Native Dutch	77.1%
Western background	9.6%
Non-western background	13.2%
Mean(SD) age	35.8 (9.83)
Mean(SD) % time in employment	82.1 (17.21)
Mean(SD) number of employer changes	4.6 (1.98)
Mean(SE) duration until permanent employment	13.3 (0.23)
Mean(SD) income (€)	1917 (799)
SD(SD) income (€)	518 (393)
Discrepancy	139.0
Turbulence	9.94

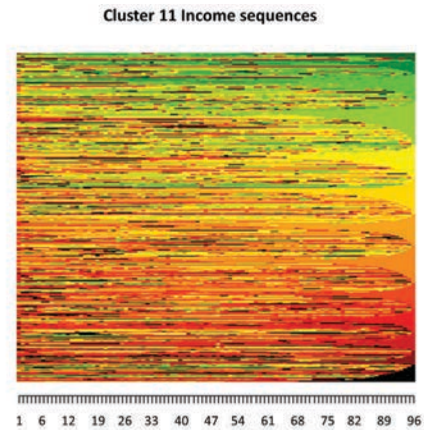
Description

The individuals in this cluster have careers that are characterized by relatively quick transitions from fixed-term employment to permanent employment. However, these permanent jobs do not last: all individuals enter another labour market position after the initial permanent job. For quite some, this is a new temporary job, but other become unemployed in the end. On average, these individuals spend 82% of their career in employment, and change employers 4.6 times on average. The employment security is thus not too high, but also not very low, as the individuals spend quite some time in permanent employment.

The incomes earned in this cluster are mixed, and while some experience an income increase, others earn less at the end of the observation period. One could say that for some individuals in this cluster, the return to temporary employment was a voluntary job switch leading to higher incomes, whereas for others leaving the permanent job may not have been voluntary.

Cluster 11: Forever Flexible





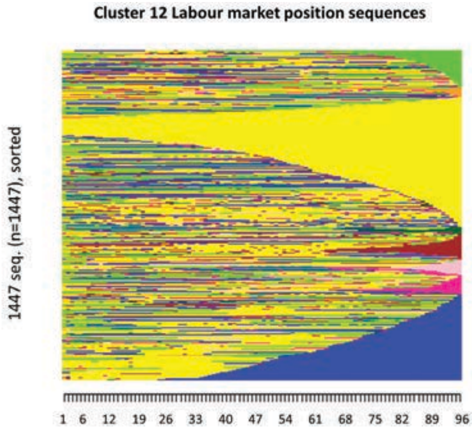
Characteristics	
N of current sample	5158
Mean % of 10 samples	9.94%
% of current sample	11.57%
Male	42.2%
Female	57.8%
Education missing	37.6%
Low education	31.6%
Average education	50.1%
High education	18.3%
Native Dutch	74.4%
Western background	9.5%
Non-western background	16.1%
Mean(SD) age	35.3 (10.26)
Mean(SD) % time in employment	82.4 (17.49)
Mean(SD) number of employer changes	4.8 (2.11)
Mean(SE) duration until permanent employment	53.5 (0.54)
Mean(SD) income (€)	1515 (721)
SD(SD) income (€)	496 (452)
Discrepancy	147.1
Turbulence	11.21

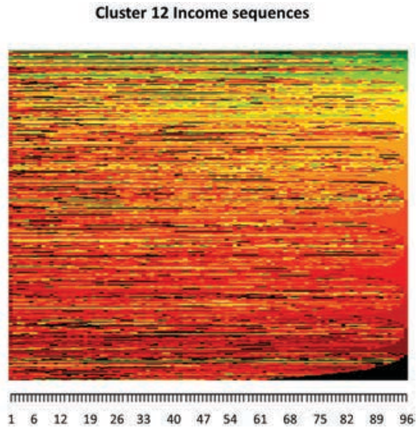
Description

Individuals in this cluster are characterized by the fact that many spend most of their careers in fixed-term employment. Many individuals change labour market positions at some points in time, making their careers quite turbulent. The individuals in this cluster also experience periods of unemployment, as the time spent in employment is 82.4% on average. Compared other clusters, these individuals also change employers relatively often, with 4.8 employer changes during the career on average. The employment security in this cluster is thus quite low.

The incomes in this cluster are also on the lower side, with an average of around €1500 monthly. The incomes also vary relatively often within careers, which is reflected in the relatively high standard deviation of almost €500. In this cluster, it is much less obvious that this large standard deviation can be explained mostly by income increases. In this cluster, it is more likely that the incomes in general tend to fluctuate over time. This makes this cluster relatively precarious both in terms of income security and employment security.

Cluster 12: Ongoing On-call





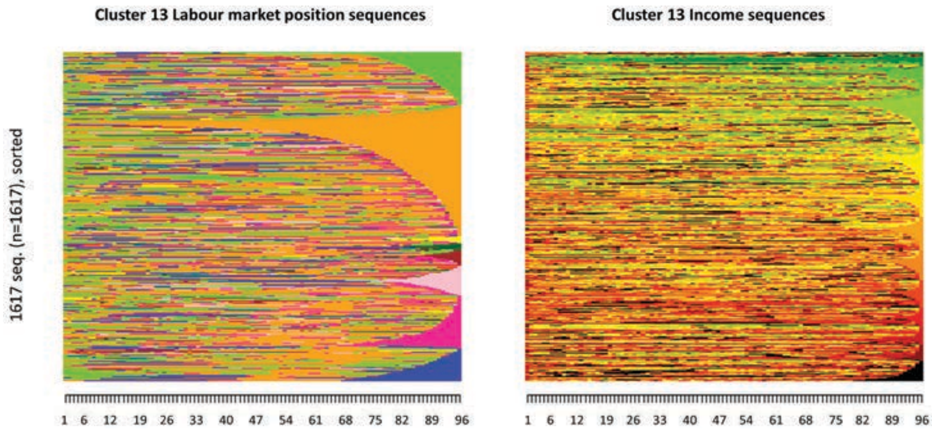
Characteristics	
N of current sample	1447
Mean % of 10 samples	2.63%
% of current sample	3.91%
Male	24.7%
Female	75.3%
Education missing	51.9%
Low education	38.8%
Average education	48.3%
High education	12.9%
Native Dutch	76.8%
Western background	9.2%
Non-western background	14.0%
Mean(SD) age	37.9 (10.99)
Mean(SD) % time in employment	88.2 (13.94)
Mean(SD) number of employer changes	4.5 (2.25)
Mean(SE) duration until permanent employment	53.0 (1.01)
Mean(SD) income (€)	1001 (619)
SD(SD) income (€)	400 (253)
Discrepancy	149.5
Turbulence	12.03

Description

The individuals in this cluster spend most of their career in on-call employment. A few of them remain in on-call employment for the entire observation period. This is possible because on-call work can be permanent employment. For some on-call individuals, the on-call job is a stepping stone to permanent employment. During their careers, the individuals are in employment 88% of the time. This is less than individuals in cluster 1 through 7, but for instance more than individuals in *Forever flexible*. Furthermore, individuals change employers 4.5 times on average, which again is more than in cluster 1 through 7, but less than the individuals in *Forever flexible*. It can thus be concluded that the workers in this cluster experience slightly more employment security than workers in *Forever flexible*.

However, the incomes earned in these jobs are on the lower side, around €1000 monthly on average. These incomes fluctuate throughout the career with €400. Compared to the mean income, that is quite a lot, decreasing the income security of these individuals even more.

Cluster 13: Temporary Work Agency Track



Characteristics	
N of current sample	1617
Mean % of 10 samples	4.00%
% of current sample	3.63%
Male	66.1%
Female	33.9%
Education missing	38.2%
Low education	38.7%
Average education	51.1%
High education	10.2%
Native Dutch	63.6%
Western background	11.1%
Non-western background	25.4%
Mean(SD) age	34.6 (10.30)
Mean(SD) % time in employment	77.1 (16.39)
Mean(SD) number of employer changes	5.5 (2.10)
Mean(SE) duration until permanent employment	61.9 (0.96)
Mean(SD) income (€)	1454 (534)
SD(SD) income (€)	579 (229)
Discrepancy	153.4
Turbulence	15.33

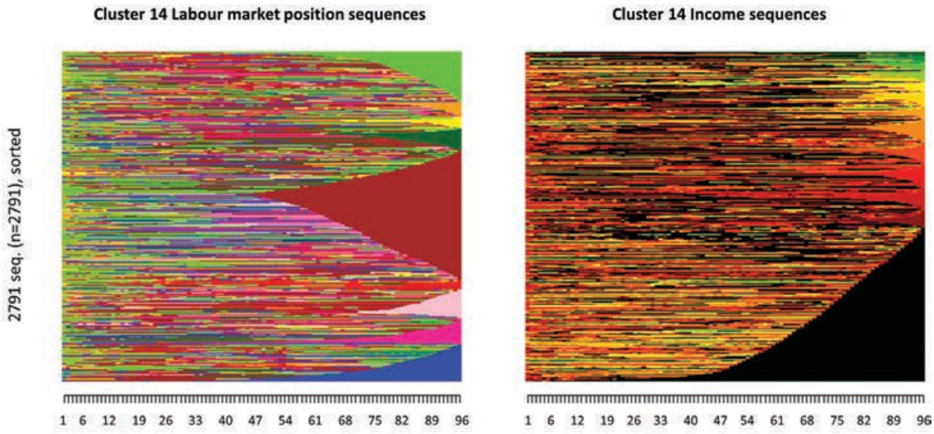
Description

In this cluster, individuals spend most of their career in a temporary work agency job. In many cases, individuals experience several labour market transitions between these temporary work agency jobs and other labour market positions, making the careers very volatile. Furthermore, individuals in this cluster only spend 77% of their career in employment. This is the lowest of all clusters in which employment has a central position. These individuals also change employers most often, on average 5.5 times during the career. This might be an underestimate, as we do not have information about the company where temporary work agency workers are sent to, but only about for which temporary work agency they work. All in all, the employment security in this cluster is very low.

The incomes in this cluster are also very volatile and vary from month to month. In general, the incomes are on the lower side, around €1500 monthly on average. These incomes fluctuate with on average almost €600, which is quite a lot given the mean income. Taking this all together, individuals in this cluster have a very precarious position both in terms of employment security as well as income security.

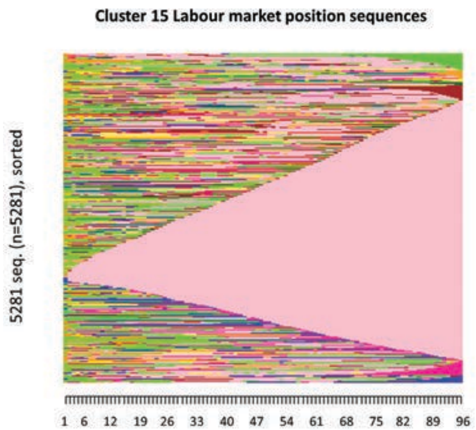
In general, the careers in this cluster are the most volatile of all clusters, with a turbulence of 15.33, and also the most heterogeneous, given the discrepancy of 153.4.

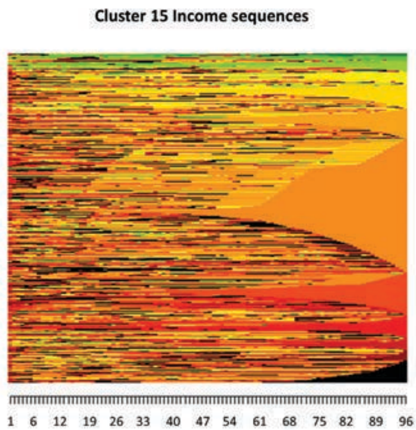
Cluster 14: Inactive Intermezzo



Characteristics		Description
N of current sample	2791	Careers in this cluster are characterized by periods of inactivity. In general, workers spend only half of their careers in employment. Most of the other time is spent in inactivity. These inactive intermezzo's could be explained by individuals leaving the labour force temporarily to get and raise children. The incomes in this cluster are quite mixed, indicating that these periods of inactivity do not depend fully on income. Lower incomes are however relatively overrepresented in this cluster.
Mean % of 10 samples	5.44%	
% of current sample	6.26%	
Male	37.2%	
Female	62.8%	
Education missing	42.0%	
Low education	40.2%	
Average education	43.8%	
High education	16.0%	
Native Dutch	62.2%	
Western background	12.6%	
Non-western background	25.3%	
Mean(SD) age	33.2 (10.72)	
Mean(SD) % time in employment	47.5 (20.23)	
Mean(SD) number of employer changes	3.4 (2.01)	
Mean(SE) duration until permanent employment	54.8 (0.75)	
Mean(SD) income (€)	1070 (843)	
SD(SD) income (€)	562 (678)	
Discrepancy	153.1	
Turbulence	14.26	

Cluster 15: Way to Welfare



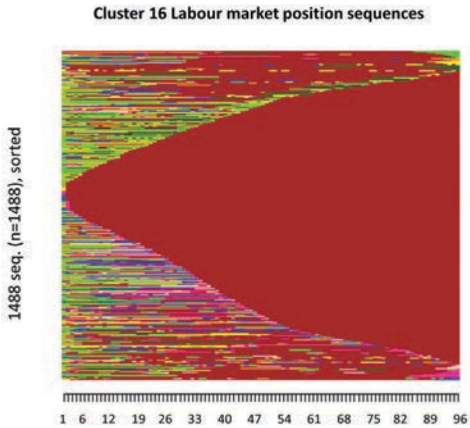


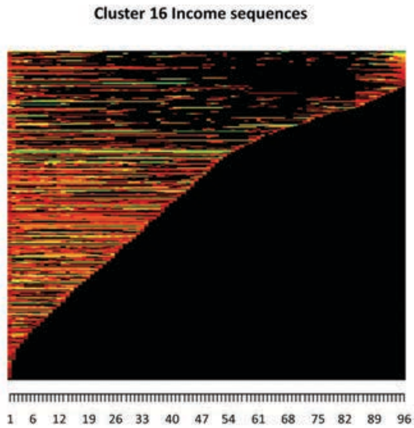
Characteristics	
N of current sample	5281
Mean % of 10 samples	10.33%
% of current sample	11.85%
Male	55.0%
Female	45.0%
Education missing	42.0%
Low education	55.4%
Average education	36.9%
High education	7.7%
Native Dutch	56.7%
Western background	10.3%
Non-western background	33.0%
Mean(SD) age	36.7 (10.81)
Mean(SD) % time in employment	25.4 (18.54)
Mean(SD) number of employer changes	2.2 (1.73)
Mean(SE) duration until permanent employment	69.3 (0.53)
Mean(SD) income (€)	1103 (524)
SD(SD) income (€)	547 (578)
Discrepancy	133.5
Turbulence	10.25

Description

The common shared factor in the careers in this cluster is a transition to welfare benefits, either on the short term or on the longer term. A few individuals manage to leave the welfare benefits after a certain amount of time and enter temporary employment again. The share of permanent employment is also quite low in this cluster. The income level of these individuals is mixed, but in general around €1100 monthly. Quite some individuals experience periods in which they have no income at all. The employment security of this cluster is very limited, but as these individuals receive welfare benefits, they have some income security.

Cluster 16: Itinerary to Inactivity



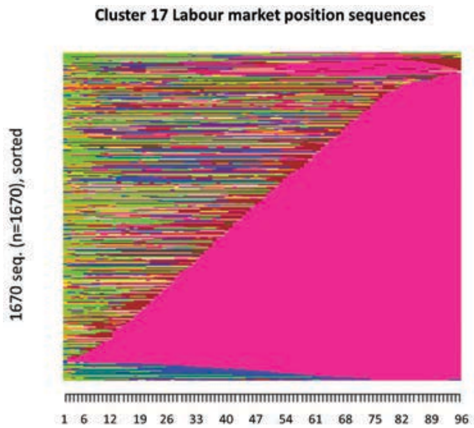


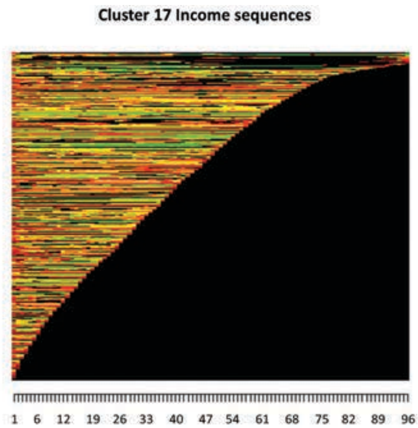
Characteristics	
N of current sample	1488
Mean % of 10 samples	3.54%
% of current sample	3.34%
Male	21.4%
Female	78.6%
Education missing	54.4%
Low education	43.4%
Average education	39.8%
High education	16.8%
Native Dutch	65.5%
Western background	11.4%
Non-western background	23.1%
Mean(SD) age	39.1 (11.11)
Mean(SD) % time in employment	16.6 (13.22)
Mean(SD) number of employer changes	1.7 (1.45)
Mean(SE) duration until permanent employment	68.8 (1.04)
Mean(SD) income (€)	797 (1439)
SD(SD) income (€)	428 (1179)
Discrepancy	60.6
Turbulence	8.21

Description

In this cluster, individuals begin their careers in fixed-term employment, but after a relatively short period of time their leave the labour market. For most, this is a final labour market transition. Some workers change between inactivity and other labour market positions, but most of their careers they spend in inactivity. When the individuals leave the labour force, they generally do not have an income. When an income is earned, these are generally on the lower side, though a few earn higher incomes of around €2000 monthly.

Cluster 17: Unfortunate Unemployed





Characteristics	
N of current sample	1670
Mean % of 10 samples	3.83%
% of current sample	3.75%
Male	57.4%
Female	42.6%
Education missing	53.0%
Low education	33.5%
Average education	39.4%
High education	27.1%
Native Dutch	42.6%
Western background	23.1%
Non-western background	34.3%
Mean(SD) age	36.0 (10.56)
Mean(SD) % time in employment	23.5 (19.80)
Mean(SD) number of employer changes	2.1 (1.60)
Mean(SE) duration until permanent employment	64.5 (1.01)
Mean(SD) income (€)	1445 (1288)
SD(SD) income (€)	544 (710)
Discrepancy	88.4
Turbulence	8.52

Description

This cluster is characterized by very unfortunate careers, namely the ones that end in unemployment. Though some individuals enter permanent employment after the temporary job they started with, these jobs do not last. On average, individuals in this cluster spend less than 25% of their career in employment.

Most individuals do not have an income once they are unemployed. Interestingly, the incomes before becoming unemployed are relatively mixed, indicating that becoming unemployed can happen to anyone.

3

The impact of fields of study on school-to-work trajectories

The interplay between educational specificity, level and cyclical sensitivity

Abstract

This chapter investigates how the specificity of the field of study determines the quality of school-to-work transitions. We contribute to the literature in two major ways. Firstly, we study whether the role of specificity in the school-to-work transition is moderated by the level of education and the cyclical sensitivity of the field of study. Secondly, we apply a processual approach in the study of the school-to-work transition. Specifically, we produce a typology of school-to-work transitions based on labour market positions and incomes. This is done with multichannel sequence analysis on register data on school-leavers in the Netherland for the 2009-2010 cohort (N=182,057). The results confirm that specificity positively influences the quality of school-to-work transitions in terms of employment and income security. This however mostly holds for the highest levels of upper-secondary vocational education (ISCED 354), while much less for the lower levels of upper-secondary vocational education and almost not at all for tertiary education. In contrast to our expectations, the positive effects of specificity were stronger for more cyclically sensitive fields of study.

This chapter is based on: Mattijssen, L., Pavlopoulos, D. & Smits, W. (2021). When does a specific field of study pay off? The interplay between educational specificity, level and cyclical sensitivity. Unpublished manuscript.

3.1. Introduction

The school-to-work transition is a crucial phase in life as it sets the stage for the development of the rest of the career (Brzinsky-Fay, 2007). Education has been identified as a driver of inequalities in this transition for a long time (Collins, 1979; Shavit & Muller, 1998). Whereas the original focus of research was mostly on vertical educational stratification and thus on the impact of the *level* of education on school-to-work transitions (Van de Werfhorst, Sullivan, & Cheung, 2003; Van der Velden & Wolbers, 2003), recently attention has shifted to 'horizontal' educational stratification: the differences in the quality of the school-to-work transition that are created by *fields* of study (Ballarino & Bratti, 2009; Markus Klein, 2011; Van de Werfhorst & Kraaykamp, 2001). The origin of the justification of this shift lies within human capital theory: skills that students acquire in different fields of study do not only differ in level, but also in specificity of resources (Becker, 1993). Different fields of study can provide general skills - i.e. skills that increase productivity in a large number of occupations -, specific skills - i.e. skills that increase productivity only in a limited number of occupations -, or a mix of these two types of skills.

Many studies have found that following a field of study that provides more specific skills can positively influence various employment outcomes, such as employment probability (Forster & Bol, 2018; Hanushek, Schwerdt, Woessmann, & Zhang, 2017), job quality (Leuze, 2007) and wages (Eggenberger, Rinawi, & Backes-Gellner, 2018). These findings can be explained by three mechanisms. The first mechanism is related to human capital: graduates of educational fields that provide specific skills are more productive in occupations that require these skills, and are in turn more attractive to the relevant employers (Becker, 1993). The second mechanism is social closure: fields that provide specific skills are more likely to provide access to credentialized occupations (Collins, 1979). The third mechanism is related to the signalling function of the field of study: rather than providing graduates with productive skills, fields of study mostly send signals about the quality of graduates (Thurow, 1975). Depending on the institutional context, this can either benefit or disadvantage graduates from specific fields of study (Barone & Schindler, 2014; Iannelli & Raffe, 2007).

Although these studies have been very insightful, they leave several theoretical matters unaddressed. For instance, previous research has typically assumed that the effect of specificity is homogeneous across levels of education. However, in coordinated labour markets, such as the Netherlands, specificity may lead to even more favourable labour market outcomes for graduates of those educational levels in which employers are institutionally involved in the design for educational programs. In more detail, in coordinated labour markets, levels of education often differ in the extent to which employers are involved in the development and delivery of education, resulting in different designs of education programs. The Netherlands are a prototypical example of such an institutional environment: employers are more involved in upper-secondary, vocational levels of education and less so in tertiary education (Marginson, Weko, Channon, Luukkonen, & Oberg, 2008). As employer involvement strengthens the effect of specificity (Iannelli & Raffe, 2007), this may have as a consequence that specificity has a stronger effect in upper-secondary, vocational education.

Earlier research has also largely omitted the fact that the role of specificity in the school-to-work transition is sensitive to economic fluctuations. In economic downturns, the positive effects of specificity may be weaker for fields that are sensitive to economic fluctuations. Specific skills make it more difficult for graduates to switch to other fields when labour demand decreases, while this is easier for graduates with general skills (Hanushek et al., 2017). So, when fields that are sensitive to economic fluctuations are faced with an economic downturn, graduates with general skills are more flexible than graduates with specific skills. For instance, let us compare two fields of study that are both sensitive to economic fluctuations, but one provides more specific skills (e.g. carpentry) and the other provides more general skills (e.g. ICT support). During an economic downturn, ICT support workers would fare better as they are more flexible due to their general skills and could easily switch to sectors that are less affected by the economic downturn. In contrast, carpenters are less flexible due to their specific skills, making it more likely that they will have more difficulties finding (matching) employment. Accounting for cyclical conditions is therefore of great importance in determining the effect of specificity.

In this chapter, we will address these theoretical issues by investigating the interaction between specificity of the field of study and level of education, as well as the interaction between specificity and cyclical sensitivity of the field of study. For this purpose, we will focus on a cohort of school-leavers in the Netherlands who entered the labour market in 2009-2010, the first phase of the Great Recession. With this ‘crisis-cohort’, including cyclical sensitivity allows us to investigate to what extent the effect of specificity changes for fields that are affected by the economic downturn, compared to fields that are unaffected by the economic crisis.

Next to the theoretical contributions, we will also improve on the methodology used in previous research on the effects of specificity on school-to-work transitions. First of all, research has overlooked the fact that the school-to-work transition cannot be adequately described as a single event. Due to imperfect information on both the employer’s and graduate’s side, achieving an optimal job match is a long-term process.

It may take some time and several job transitions before the right employer-employee match is made (Jovanovic, 1979). Brzinsky-Fay (2007) convincingly argues that the school-to-work transition should not be studied as a single point-in-time event, but rather as a *process* that includes all events that occur in the period that it covers, the order of these events as well as the duration between two subsequent events. Otherwise, the complexity of the school-to-work transition may be underestimated (Brzinsky-Fay, 2014), especially in contexts of increasingly flexible labour markets in which jobs for life are becoming less and less common. Therefore, he suggests that a processual or trajectory approach is more appropriate in studying the school-to-work transition. Recent labour market studies have illustrated that such a processual approach leads to novel insights (Mattijssen, Smits, & Pavlopoulos, 2018). The most commonly used method in processual approaches is sequence analysis (Abbott & Tsay, 2000). Many recent studies have used sequence analysis for studying various life-course events (Aisenbrey & Fasang, 2017; Fuller & Stecy-Hildebrandt, 2015).

Although the use of a processual approach is not new for the study of school-to-work transitions (Berloffa, Matteazzi, Mazzolini, Şandor, & Villa, 2019; Dorsett & Lucchino, 2014), relevant studies are restricted to one dimension of the school-to-work transition. In more detail, these studies construct typologies of school-to-work transition patterns on the basis of employment status only (Middeldorp, Edzes, & Van Dijk, 2019). However, employment status by itself cannot fully describe the quality of a school-to-work transition. Young workers often trade employment security with income security: some choose employment pathways with insecure contracts that offer a high compensation, or vice versa. Therefore, comparing the quality of school-to-work transition of e.g. a high-paid consultant who is employed with a fixed-term contract with a low-paid secretary who is employed with a permanent contract, requires that both dimensions of the process of school-to-work transition – i.e. employment status and income – are evaluated.

Secondly, a methodological shortcoming of previous research on the effect of specificity in the school-to-work transition is the operationalization of specificity itself. In more detail, these studies typically introduce a crude dichotomy between ‘general’ and ‘specific’ fields of study (Hanushek et al., 2017; Middeldorp et al., 2019). However, there is large variation in specificity within the two groups of this dichotomy (Forster & Bol, 2018). An objective, continuous measure of specificity would therefore be better suited to properly investigate the effects of specificity. DiPrete et al. (2017) have recently developed such a continuous approach to measure the specificity of the field of study. This measure is an expression of the extent to which graduates from a specific field of study are spread over occupations, relative to how graduates, independent of field of study, are spread over occupations. Their procedure resulted in an objective, continuous measure of specificity. Though several studies have now used this scale to assess the effect of specificity on school-to-work transitions (Forster & Bol, 2018; Rözer & Bol, 2019), this measure of specificity has not yet been used in combination with a processual approach.

To sum up, our methodological contribution is twofold. Firstly, we use a procuessual approach and simultaneously study two dimensions of school-to-work transition (employment status and income) with *multichannel sequence analysis*. Secondly, we use a continuous measure of specificity to assess the extent to which specificity influences membership to the typology of school-to-work transition patterns that is produced by multichannel sequence analysis (DiPrete et al., 2017; Forster & Bol, 2018). Together with the theoretical contributions of taking into account the interplay between specificity, level of education and cyclical sensitivity, our approach will give new and more nuanced insights in how specificity affects the school-to-work transition.

3.2. Theoretical framework

3.2.1. Specificity of the field of study and school-to-work transitions

Fields of study vary in the types of skills they provide students. In his seminal work, Becker distinguishes between general skills and specific skills (Becker, 1993). General skills (e.g. analytical thinking) raise productivity in a wide variety of jobs. This means that these skills can be applied in a large array of occupations, making these skills very transferable. In contrast, specific skills (e.g. carpentry) raise productivity in a limited number of jobs, occupations or firms.

There are three mechanisms via which the types of skills provided by the field of study may impact the school-to-work transitions of school-leavers. First, *human capital theory* (Becker, 1993) argues that some fields of study may develop more productive skills than others. Graduates from those fields that provide more productive skills consequently require less on-the-job training when employed and are more productive than graduates from fields that do not provide these productive skills. These reduced training costs and higher productivity make graduates from these fields more attractive for employers (Lombardo, De Luca, & Passarelli, 2012; Middeldorp et al., 2019). Graduates from more specific fields of study are preferred by employers for jobs in which these specific skills increase productivity the most. In these occupations, specific skills reduce training costs for employers (Leuze, 2007). This would result in better school-to-work transitions for graduates of specific fields of study.

Second, *social closure theory* argues that education pays off by limiting access to occupations to graduates from certain fields of study (Collins, 1979). This improves the employment outcomes of graduates in these fields, not only because they have the mandatory skills for the occupation, but also because they are the only ones who are allowed to apply those skills. In turn, this results in scarcity (Bol & Weeden, 2015; Van de Werfhorst, 2011). Generally, fields of study that ensure access to occupations with high levels of social closure are mostly fields that provide students with occupation-specific credentials (Bol & Weeden, 2015). This would mean that specific fields of study would lead to better labour market outcomes.

Lastly, *job competition theory* argues that labour productivity is mainly developed through on-the-job training (Thurow, 1975). The skills acquired in formal education are less relevant for productivity. However, the field of study can still function as a signal of ability, trainability and motivation. Employers use this signal as a screening device for new hires (Spence, 1973). Job competition theory however remains ambiguous about what kind of signal specific skills provide. On the one hand, graduating from a more specific field could be interpreted by employers as a signal of high quality, as more specific fields are often considered to be more challenging than more general fields (Reimer, Noelke, & Kucel, 2008). Graduates from more specific fields of study would also be more motivated to work in the matching occupations than graduates from more general fields of study, making these former more attractive for employers as well (Barone & Schindler, 2014). On the other hand, employers could prefer academic, general education over specific, vocational education as the latter is associated with lower levels of both ability and motivation (OECD, 2010). The direction of the signalling effect of specific education seems to depend on the institutional context and the design of the education system (Iannelli & Raffe, 2007).

3.2.2. Level of education, institutional context and school-to-work transitions

The relevance of horizontal educational stratification (i.e. the type of skills acquired in a particular field of study) does not undo the importance of vertical educational stratification. Naturally, the level of skills matters as well: high level skills lead to higher productivity, offer access to many occupations that have minimum entry requirements that are related to skill level, and signal higher trainability. This explains why higher levels of education result in better employment outcomes (Becker, 1993; Shavit & Muller, 1998). However, level of education does not only have a direct effect: in certain institutional contexts, the level of education can also diversify the effect of specificity.

Many studies have investigated the influence of the institutional context on the effect of specificity on employment outcomes and concluded that the effect of specificity depends on the institutional context, in which the education system plays an important role (Allmendinger, 1989; Bol et al., 2019; Korpi, De Graaf, Hendrickx, & Layte, 2003; Olsthoorn, 2016; Reimer et al., 2008; Wolbers, 2007). Like Germany, Austria and Switzerland, the Netherlands are considered to be a coordinated market economy (CME) with a strongly regulated labour market (Hall & Soskice, 2001). This high level of coordination positively influences the employment outcomes for graduates from specific fields of study: collective agreements between employers, trade unions and the state lead to regulated access to occupations, on the condition of obtaining degrees from certain fields of study. Graduating from these fields, that are likely to provide the specific skills required by employers, leads to improved employment outcomes (Bol and Van de Werfhorst 2011).

Moreover, the Dutch education system is highly stratified, highly differentiated and highly standardized. This means that in general, the level of education and the field of study are direct quality indicators for employers, benefitting graduates from specific fields of study (Iannelli & Raffe, 2007). Furthermore, the high level of coordination does not only result in a high level of regulation of access to occupations, but also in a strong link between employers and the education system. Employers are often actively involved in the development of education programs, and also often host students in their firms through apprenticeships or internships (Onstenk, 2017). This strong linkage especially benefits students from more specific fields of study, who acquire on-the-job the skills that employers require them to have when they enter the labour market. These characteristics of the Dutch education system thus have as a consequence that fields of study are clear signals of the type of skills that graduates possess (Iannelli & Raffe, 2007). Graduating from a specific field is not only a signal of trainability, but actual evidence that the young worker possesses productive skills required on the job (Barone & Van de Werfhorst, 2011; Bol & Van de Werfhorst, 2011). A more detailed description of the Dutch education system can be found in Appendix 3A.

The involvement of employers is, however, not the same in all levels of education. The education-employment linkage is the strongest at the upper-secondary vocational levels of education (ISCED 353/354). In these levels, fields of study involve dual systems in which students learn while working in firms, and employers are strongly involved in curriculum design. For instance, the Netherlands have one national organization, the Foundation for Cooperation on Vocational Education, Training and Labour Market (SBB), which has the legal obligation to advise, accredit and oversee work placement companies and to develop and maintain the qualification structure of upper-secondary vocational education (ISCED 353 and 354), in cooperation with employers. In contrast, for tertiary education (ISCED 646/656, ISCED 747/757), the connection between fields of study and the labour market is often weaker and much less formalized than at the upper-secondary levels of education (Marginson et al., 2008). Dual systems are less common and on-the-job training mostly takes place during (optional) internships that are a relatively small part of education programs. Moreover, these internships usually cannot be arranged using pre-existing relations between employers and education programs, but have to be arranged by students themselves. Specificity at tertiary levels of education is thus less of a strong signal of quality for employers. This means that for employers of new hires with tertiary education, there is relatively less direct information on the skills of these school-leavers and the chance of a mismatch is higher. This is likely to result in weaker effects of specificity at the tertiary levels of education (De Lange, Gesthuizen, & Wolbers, 2014).

Summarizing, the highly coordinated Dutch labour market institutions clearly facilitate smooth school-to-work transitions for graduates from specific fields of study, but likely more so for the levels of education in which connections between education and employers are strongest (ISCED 354). However, research has hardly focussed on the possible moderating effect of the level of education in coordinated labour markets. The effect of specificity is in some cases studied separately for various levels of education (Bol et al., 2019; Korpi et al., 2003). Interactions between level of education and specificity are also occasionally found in comparative research on the vocational specificity education systems (De Lange et al., 2014). In research on the specificity of fields of study, there is also little attention for the interplay between educational specificity and the level of education. In their study of occupational status, Bol and Van de Werfhorst (2011) include an interaction between level of education and importance of vocational programs in economic sectors. They however focus on how the effect of level of education on occupational status differs per level of importance of vocational programs, and do not discuss the reverse of how the effect of importance of vocational programs differs per level of education. They find that the effect of level of education on occupational status is stronger when vocational programs are more important in an economic sector.

As studies that empirically test whether the effect of specificity of fields of study on school-to-work transitions is moderated by level of education are scarce, this chapter aims to fill this gap in the literature. In the context of this study, we expect that:

- specificity results in school-to-work transitions with higher levels of both employment and income security (*hypothesis 1*),
- the effect of specificity is stronger for fields of study at the upper-secondary levels of education, in particular at the ISCED 354 level (*hypothesis 2)*.

3.2.3. How cyclical sensitivity can moderate the effect of specificity on school-to-work transitions

Specific skills increase productivity in some occupations while they are irrelevant for a large number of other occupations. Returns to specific skills largely depend on successfully finding a job in a matching occupation. When the demand for graduates from a specific field of study is sensitive to economic fluctuations, the risk of not finding a matching occupation increases when entering the labour market during a period of economic downturn. These graduates face an increased risk of underemployment or even unemployment. This in turn leads to skill depreciation (Van Loo, De Grip, & De Steur, 2001). Such a suboptimal labour market entry may have long-term consequences for their employment and income security.

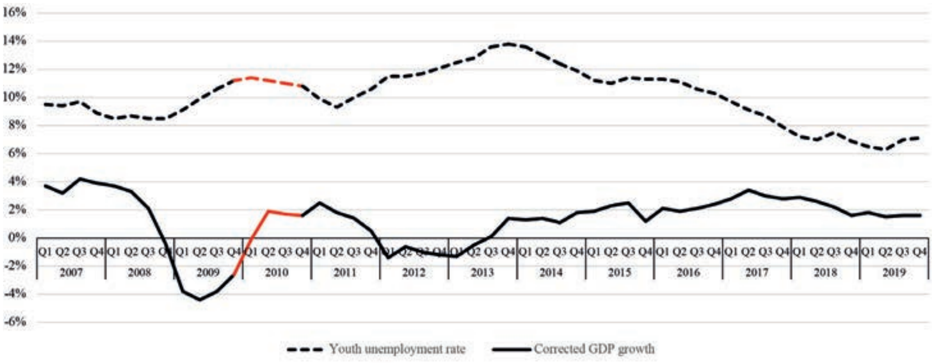
The effect of sensitivity to the business cycle can be identified only in a period of economic downturn. During an economic upturn, specificity always pays off. Irrespective of cyclical sensitivity, graduates from more specific fields of study are more likely to have higher levels of employment security in their school-to-work transition: they find employment in a matching occupation quickly, as they are preferred by employers and are less likely to be screened with a temporary contract as employers have more certainty about their productivity (Giesecke & Schindler, 2008; Lombardo et al., 2012). They also have higher levels of income security in their school-to-work transition as they are more likely to earn higher wages due to higher productivity in their matching occupations (Webber, 2014) and, as a consequence of their higher employment security, also have more income stability. In contrast, during an economic downturn, specificity pays off only for fields of study that are not cyclically sensitive. Graduates from cyclically sensitive specific fields of study risk not finding a matching occupation due to decreased labour demand. This increases their job search duration and the likelihood of a job mismatch, resulting in lower incomes. As general skills are applicable in a larger array of jobs, graduates from more general fields of study are more versatile and more likely to find matching employment, even in an economic downturn. So, in cyclically sensitive fields of study, specificity has less positive, or even negative effects, on the quality of school-to-work transitions. In contrast, cyclically insensitive fields of study would be unaffected by an economic downturn and not be confronted with lower labour demand. For these fields of study, the effect of specificity on the quality of school-to-work transitions would still be positive.

There has not been much attention to the influence of economic conditions and cyclical sensitivity in previous research. Usually, research has either studied the effects of specificity before the economic recession of 2008-2013 (Coenen, Heijke, & Meng, 2014; Middeldorp et al., 2019), or studied multiple cohorts simultaneously (Forster & Bol, 2018; Forster, Bol, & Van de Werfhorst, 2016). As far as we know, the only attempt to directly investigate how the effect of specificity is affected by economic conditions was made by Muja et al. (2019). Using data for the Netherlands, they investigated whether the effect of specificity was moderated by the regional youth unemployment rate. Contrary to what would be expected, they do not find any moderating effects of regional youth unemployment rates on the effect of specificity on several employment outcomes. Next to this, a meta-analysis by Blommaert et al. (2020) of the effect of vocational specificity of education systems gives an indication of the potential direction of the moderating effect of economic conditions. They reach the unexpected conclusion that the vocational specificity of education systems has a stronger positive effect on employment outcomes in times of high levels of unemployment. This study, however, also focuses on the specificity of education systems, and not on the within-country specificity of fields of study, which leads the authors to ask readers to take caution with these results.

In this chapter, we study a cohort that entered the labour market in 2009 or 2010, in the beginning of the Great Recession. This enables us to identify the possible moderating effect of cyclical sensitivity of the field of study. Figure 3.1 shows the development of the GDP growth and the youth unemployment rate from 2003 to 2019 to illustrate the scope of the economic recession in the Dutch context. The Dutch economy experienced relatively weak effects of the economic crisis, with the GDP shrinking 4.4% in the second quarter of 2009, which was the strongest decline in the period covered here. Though there was some minor recovery in 2010 in terms of GDP growth, the youth unemployment rates remained above pre-crisis levels and increased even further in subsequent years. In the context of our study, we expect that:

- the positive effect of specificity are weaker for more cyclically sensitive fields of study than for more cyclically insensitive fields of study (hypothesis 3).

Figure 3.1: Economic conditions in the Netherlands, 2007-2019



Red section depicts the period during which the research cohort entered the labour market. Data retrieved from CBS Statline (2019a, 2019b).

3.3. Data, variables and methods

3.3.1. Data

This chapter uses a unique register dataset to investigate the effect of educational specificity on the quality of school-to-work transitions. Specifically, we use register data from Statistics Netherlands (*'System of Social Statistical Datasets' – SSD*, see Bakker et al. (2014)) that contains micro-level information on employment, income and welfare of the 2009/2010 cohort of school-leavers in the Netherlands. These data allow for tracking the school-to-work transitions of the school-leavers from the moment they leave education until December 2016. As the cohort leaves education between October 1st 2009 and September 30th 2010, all individuals can be tracked for 72 months, allowing for a detailed longitudinal account of their school-to-work transitions. Information about the last attended type of education when leaving education was obtained from the Education Archive of Statistics Netherlands (Linder et al., 2011). This database brings information on education from several registers and the Dutch Labour Force Survey together. This Education Archive contains highly detailed information on the full education history of our cohort, including the national standardized codes (CROHO and CREBO) assigned to each unique education program (more information on these codes can be found in Appendix 3A). Information on the final education program attended before leaving education was linked to the register data at the individual level.

In the analysis, we focus specifically on school-leavers from programs that are considered to be a valid preparation for entering the labour market within the Dutch education system: upper-secondary vocational education (ISCED 353 (2 years), ISCED 353 (3 years) and ISCED 354 (4 years)), tertiary vocational education (ISCED 655 and 757) and tertiary academic education (ISCED 645 and 747). We exclude school-leavers from upper-secondary general education that intends to prepare for tertiary education (ISCED 344 (HAVO/VWO)), as the large majority of these graduates pursues further education.

Some additional sample restrictions were applied as well. As the focus is on the first school-to-work transition, school-leavers aged 30 or over were excluded, as it is unlikely that this group has not entered the labour market before. School-leavers from part-time education are excluded as well, as they usually are already employed during their study.[11] We also exclude school-leavers who return to education for 10 months or

11 Part-time students generally have a regular job on their own skill level, but pursue further education to improve their employment prospects. They are thus generally not first-time school-leavers. In the Netherlands, it is common for full-time students may be employed next to their education as well. Those jobs are however mostly not jobs that match their field and level of education, but rather more lower-skilled jobs as serving in restaurants, or re-stocking shelves in supermarkets.

more after 2010, as this indicates that the actual school-to-work transition occurred later than the 2009-2010 period. Importantly, school-leavers who leave education without a diploma in their last field of study are *not* excluded from the analyses. The final sample consists of 182,057 individuals. An overview of the number of cases that were excluded based on these latter criteria can be found in Appendix 3B.

3.3.2. Measuring educational specificity

To compute a measure of specificity, we create a *linkage* scale using the approach that was developed by DiPrete et al. (2017) and used by Forster and Bol (2018). This scale expresses the connection between field of study and occupation by taking into account the distribution of graduates over occupations. Formally, it is defined by the following equation:

$$Linkage(ed)=\sum_j p_{j|g} log\left(\frac{p_{j|g}}{p_j}\right) \qquad (1)$$

where $p_{j|g}$ is the probability of having occupation j given field of study g and p_j is the probability of having occupation j independent of field of study. A high score on the scale indicates that the field of study is strongly connected to only few occupations.

To calculate specificity scores for the fields of study in our data, we use information from the Dutch Labour Force Survey from 2008 to 2010 (Statistics Netherlands, 2010). These data allow us to get a representative image of the link between the field of study and occupation. To distinguish the fields of study, we used the Dutch educational classification *Opleidingsclassificatie naar Niveau en Richting 2019* (ONR2019, Educational Classification by Level and Field). This classification allows for distinguishing between educational levels and fields, while also allowing for fields to vary between levels of education. For occupations, we used the Dutch occupational classification *Beroepenindeling ROA-CBS* (BRC2014, Occupational classification from the Research Centre for Education and the Labour Market, and Statistics Netherlands). To focus on the connection between education and occupations, we only included individuals in this analysis who were no more than 15 years older than the expected graduation age linked to their level of education (Forster & Bol, 2018). Thus, the age limit varied from 33 for ISCED 353 (2 years) to 42 for ISCED 747/757.

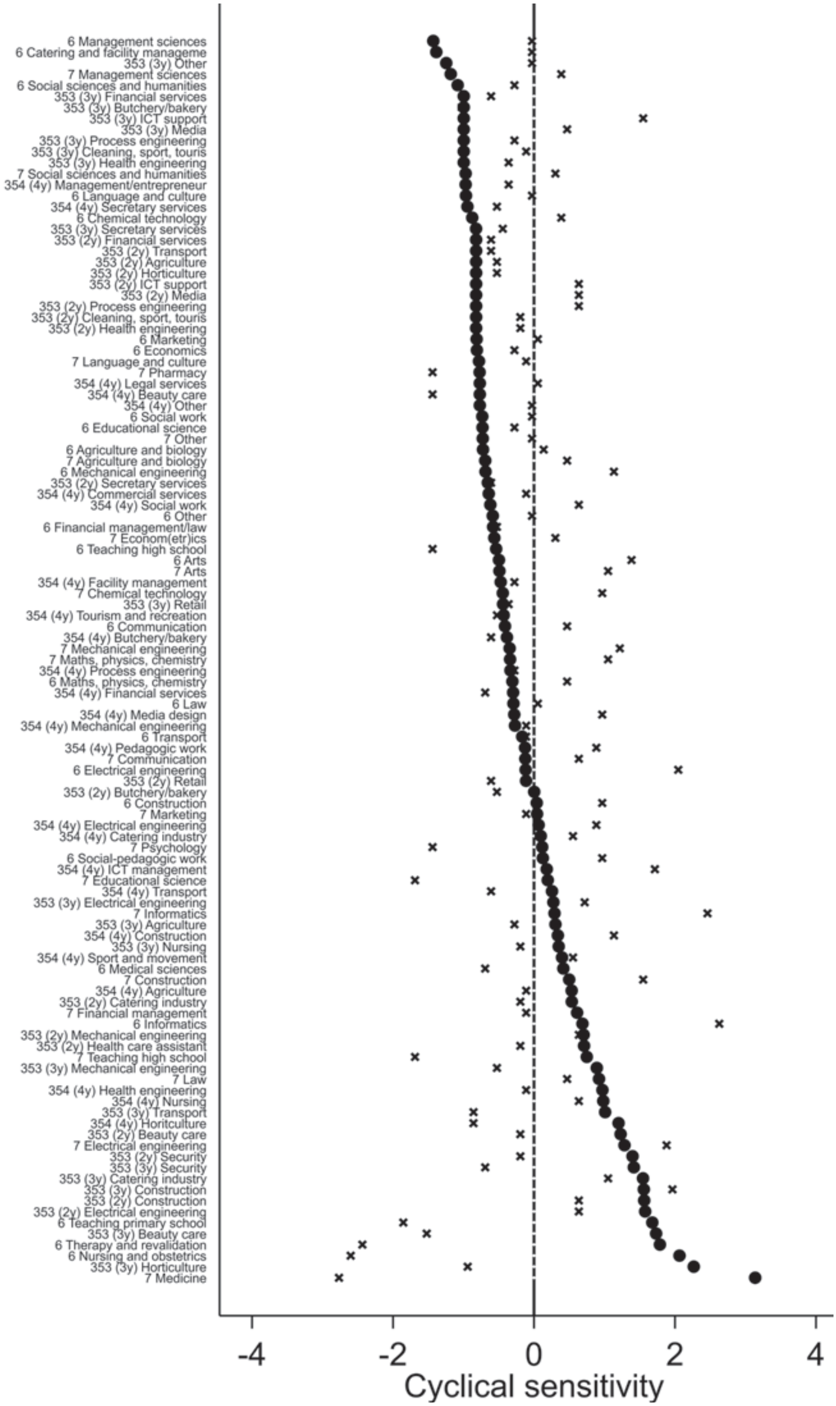
Using population weights, we calculated the mean number of workers in each education-occupation combination over those three years. If an educational or occupational category contained less than 2500 individuals in the population, this group was not included as a separate category in the construction of the scale, but was combined with other categories with too few observations as a separate category called ‘too small’. For occupations, only one ‘too small’ category was created. For fields of study, we created one ‘too small’ category for each level of education. In total, we could distinguish 97 educational categories and 93 occupations. Using these combinations, we calculated the linkage score for each educational category. This scale has a mean of 1.45 (for ISCED 353 (2 years) Retail) with a standard deviation of 0.62, a minimum of 0.52 (ISCED 645/655 Management) and a maximum of 3.50 (ISCED 747/757 Medicine). However, ISCED 747/757 Medicine is a peculiar group that indeed has a high level of specificity, but also is characterized by a practically fixed career path after finishing the Master's. Due to strong credentialization of the medical profession, most students enter long-term temporary jobs in hospitals required to specialize on the job in a particular field of medicine. Their employment outcome is therefore largely fixed by their field of study. As this could strongly bias the effect of specificity, we include a dummy variable indicating ISCED 747/757 Medicine in the explanatory analysis to take away any bias in the estimates of specificity caused by this group. For the analysis, the scale was Z-standardized. All scores on the standardized specificity scale can be found in Figure 3.2.

3.3.3. Measuring cyclical sensitivity of fields of study

Cyclical sensitivity of fields of study was measured using an existing scale developed by the Research Centre for Education and the Labour Market (ROA) (Cörvers, Dupuy, Dijksman, Kriechel, & Montizaan, 2010). This measure indicates to what extent the employment levels of a certain field of study fluctuate as a consequence of fluctuations in the employment levels of industries. In contrast to the specificity scale, we did not calculate the cyclical sensitivity scores ourselves, but used the scores produced by ROA. ROA has produced scores for all fields of study of the ONR2019 classification, the same classification as used in the construction of the specificity scale.[12] The cyclical sensitivity scale ranges from 0.67 for the least cyclically sensitive field of study (Master medicine) to 1.32 for most cyclically sensitive field of study (Bachelor informatics). For the analysis, the scale was z-standardized. The standardized scores on the cyclical sensitivity scale can be found in Figure 3.2 as well.

12 For the full operationalization of the cyclical sensitivity indicator, we refer to Cörvers et al. (2010).

Figure 3.2: Scores on the specificity and cyclical sensitivity scales (z-scores)



3.3.4. Multichannel sequence analysis

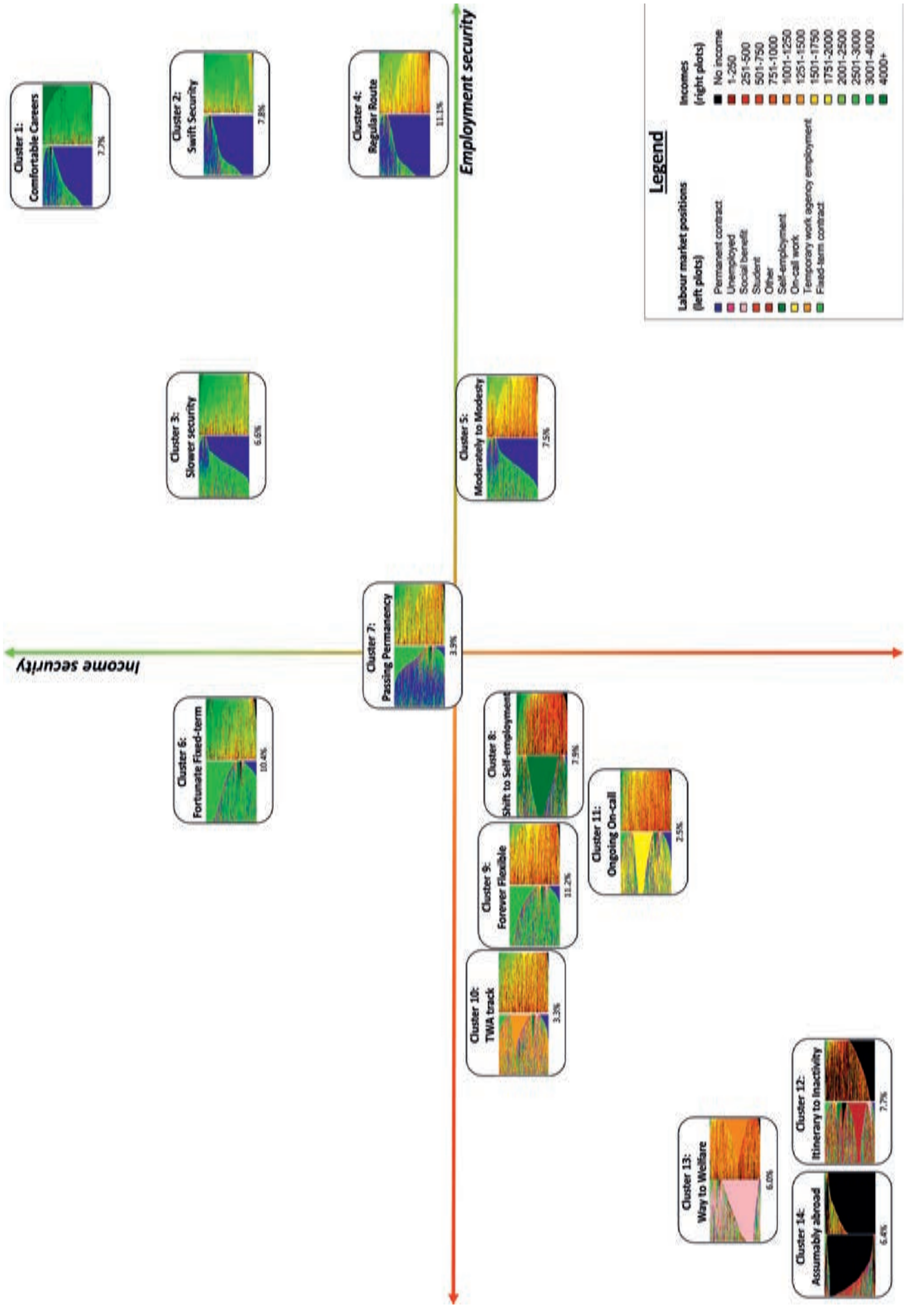
To create a typology of school-to-work transition patterns, we used multichannel sequence analysis. Sequence analysis is a statistical method that can be used to describe a series of states, such as employment positions or other longitudinal life course statuses. It first calculates the similarities of all sequences using distance measures, and then uses clustering algorithms to group the sequences in a typology (Abbott & Tsay, 2000). Multichannel sequence analysis allows for the simultaneous study of two or more sequences per individual, each of which based on a different variable. To conduct the sequence analysis the statistical software R (R Core Team, 2019) was used and in particular, the TraMineR package (Gabadinho, Ritschard, Mueller, et al., 2011) and the WeightedCluster package (Studer, 2013).

For our multichannel sequence analysis, two sequences are created per individual: one of labour market positions and one of monthly incomes. The ten labour market positions that are included in the employment sequence are: permanent contract, fixed-term contract, temporary work agency contract, on-call contract, self-employed, unemployed, receiving welfare benefits, student, inactive and unknown. As sequence analysis treats all states as discrete, income is classified into 13 categories, that are depicted in the legend of Figure 3.3. For incomes up to €2000, we use smaller income ranges for the categories, as smaller income fluctuations have larger consequences at low income levels than at high income levels: for people earning €1000 monthly, an income decrease of €250 has more impact than for people earning €4000 monthly.

The similarity of sequences is determined using the Hamming distance, which is more sensitive to differences in timing as it does not allow for inserting or deleting states (Hamming, 1950; Studer & Ritschard, 2016). This for instance prevents school-to-work transitions with quick transitions from temporary to permanent employment to be classified as similar to school-to-work transitions in which the transition from temporary to permanent employment occurs very late. Subsequently, the sequences are clustered using hierarchical Ward clustering (Ward, 1963) on the Hamming distance matrix. The number of clusters is determined qualitatively as quantitative cluster quality measures cannot be used due to extremely high heterogeneity of sequences. We instead rely on the internal replication strategy proposed by Mattijssen and Pavlopoulos (2019) to determine a reliable number of clusters.

In this replication strategy, the data were divided into four random subsamples. For each subsample, a sequence analysis was run. Then, for each sample, we constructed a typology using a Ward clustering with 20 clusters. The 20 clusters in those four samples were compared qualitatively to assess which types of clusters occurred more frequently than others and would therefore be more representative. The clusters that were found in all four samples were used as the representative clusters. This was the case for 14 clusters.

Figure 3.3: Typology of school-to-work transition patterns



For these 14 clusters, we extracted medoid sequences. Subsequently, we reran the sequence analysis for the four samples, to which the 14 medoid sequences were added. Using the distance matrix, we then assigned each original sequence to the medoid sequence to which they were most similar. This way, we could retain all individuals in the analysis. However, a problem that emerged during this procedure was that many individuals were equally most similar to more than one medoid, which complicated their classification. This was the case for 9,525 individuals. These individuals were randomly assigned to one of the medoids to which they were equally most similar. The final typology strongly resembles previous typologies that have been made using multichannel sequence analysis on different subsets of this dataset (Mattijssen & Pavlopoulos, 2019). This confirms the robustness of the typology.

3.4. Results

3.4.1. Typology of school-to-work transition patterns

As reported, the multichannel sequence analysis with internal replication resulted in a typology with 14 clusters. For interpretability, each cluster was given a name. To evaluate the school-to-work transition patterns with respect to employment and income security, we placed the clusters on a two-dimensional grid with these two dimensions (Figure 3.3). The placement of the clusters on this grid was done with a combination of qualitative and quantitative criteria. As criteria of employment security, we used mean time spent in employment, mean time spent in permanent employment and mean duration until permanent employment. As indicators of income security, we used mean within-sequence income and within-sequence standard deviation of income. However, as differences in the security provided by different employment types are difficult to quantify, these were taken into account qualitatively. These descriptive statistics per cluster are reported in Appendix 3B.

On the top right of the grid, we find four types of school-to-work transitions with high levels of employment and income security. In the clusters *Comfortable Careers*, *Swift Security* and *Regular Route*, school-leavers make the transition to permanent employment quite fast. In cluster *Slower Security*, it takes school-leavers longer to enter permanent employment after a period of employment with a fixed-term contract. All four clusters have higher levels of income security. The highest incomes are found in *Comfortable Careers* and the lowest among these four clusters in cluster *Regular Route*. *Slower Security* has lower starting incomes than *Swift Security*, but is accompanied with higher income growth, resulting in higher final incomes. Combined, these clusters contain 33.2% of the school-leavers.

On the opposite lower left side of the grid, we find the school-to-work transitions with lower levels of employment and income security. These are either characterized by non-employment in clusters *Itinerary to Inactivity* and *Way to Welfare* (combined 13.7%), but we also find school-to-work transitions in which individuals are in a precarious situation while being employed. In clusters *Forever Flexible*, *Shift to Self-employment*, *Temporary Work Agency (TWA) Track* and *Ongoing On-call*, school-leavers spend their school-to-work transition mostly in fixed-term employment, self-employment, temporary work agency employment or on-call work respectively, while earning low and unstable incomes (combined 25.0%). For them, the school-to-work transition has not been too successful. In this quadrant, we also find individuals who are *Assumably Abroad*: these individuals are at some point temporarily or permanently no longer present in the register data either because they have left the Netherlands or because they have passed away. Given the young age of the individuals in our population, it is likely that most have left the Netherlands to work or study abroad, or to return to their home country after completing their education in the Netherlands. This latter argument is supported by the relatively high number of individuals with a non-Dutch background in this cluster (see Table 3B.4 in Appendix 3B).

On the bottom right-hand side of the grid, we find one type of school-to-work transition that combines lower levels of income security with relatively high levels of employment security. School-leavers in *Moderately to Modesty* make the transition to permanent employment after some time, giving them employment security, but earn incomes that are on the lower side and increase relatively little over time. 7.5% of the school-leavers experience this school-to-work transition.

On the top left side of the grid, we find the contrary: a type of school-to-work transition that combines high levels of income security with lower levels of employment security. In *Fortunate Fixed-term*, school-leavers spend most of their time in fixed-term employment, while earning relatively high wages. Many of them also experience significant income growth in this time. So, even though they are employed with a non-permanent contract, their school-to-work transitions should not be considered as unsuccessful. 10.4% of the school-leavers go through this school-to-work transition.

Finally, one type of school-to-work transition is hard to classify, as it is characterized by a transition from permanent to fixed-term employment. *Passing Permanency* scores mixed in terms of employment security and is therefore placed in the middle. Income security in this cluster is on the higher side, but the transition from permanent to fixed-term employment has been accompanied with income increases for some, but income decreases for others. Therefore, its score on income security is also somewhat in the middle. 3.9% of the school-leavers experience a school-to-work transition like this.

3.4.2. Testing the effect of specificity on school-to-work transitions

To investigate the effect of educational specificity on the school-to-work transition, the 14 clusters resulting from the multichannel sequence analysis were used as the dependent variable in a multinomial logistic regression. The main independent variable in these regressions is specificity, measured with the z-standardized linkage scale described in section 3.3.2. Level of education was included in the analysis as a categorical variable. We distinguished between all six levels of education mentioned in section 3.3.1. Due to the small number of graduates at the ISCED 757 level, this group was combined with graduates at the ISCED 747 level. To assess whether the effect of specificity is different per level of education, we included an interaction term between specificity and level of education in the analysis. The cyclical sensitivity scale, described in section 3.3.3, was included in the analysis as a continuous indicator as well. To assess whether the effect of specificity is dependent on cyclical sensitivity, an interaction effect between specificity and cyclical sensitivity was included in the analysis.

As controls, we included a dummy variable for studying in a dual system (work-based learning) in upper-secondary education. As stated before, we also included a dummy variable indicating Master level Medicine, as this field scores high on specificity, but also is accompanied with fixed career paths. Furthermore, a variable indicating whether the school-leaver has completed the degree of their last education was included in the analyses. We also included dummy variables for field of study, to separate the effect of specificity from other possible confounding effects of the field of study. For this purpose, we used the 1-digit version of the Dutch educational classification *Standaard Onderwijsindeling* (SOI). Unlike the ONR2019, this educational classification only distinguishes between nine fields of study, that do not differ between levels of education. As further controls, age, gender and migration background were included, as these are known to affect employment outcomes, with younger workers being more likely to remain in flexible employment for a longer period of time, women to be more likely to have lower monthly incomes due to part-time work and higher probabilities of entering inactivity, and workers with non-western migration backgrounds to be more likely to enter more precarious careers in terms of both employment and income security (Mattijssen & Pavlopoulos, 2019).

2.4.3. Effects of specificity on school-to-work transitions

The results of the multinomial logistic regression are presented using average marginal effects (Mize, 2019). These can be interpreted as the percentage point (pp) increase in the probability of experiencing a certain type of school-to-work transition per unit increase of the independent variable. The effects for specificity, level of education, cyclical sensitivity and their interactions can be found in Table 3.1. The full results including all covariates can be found in Appendix 3C. For illustration, we also illustrate the average marginal effects in the grid of the typology (Figure 3.4).

Figure 3.4: Average marginal effect of specificity on the probability of experiencing the types of school-to-work transitions

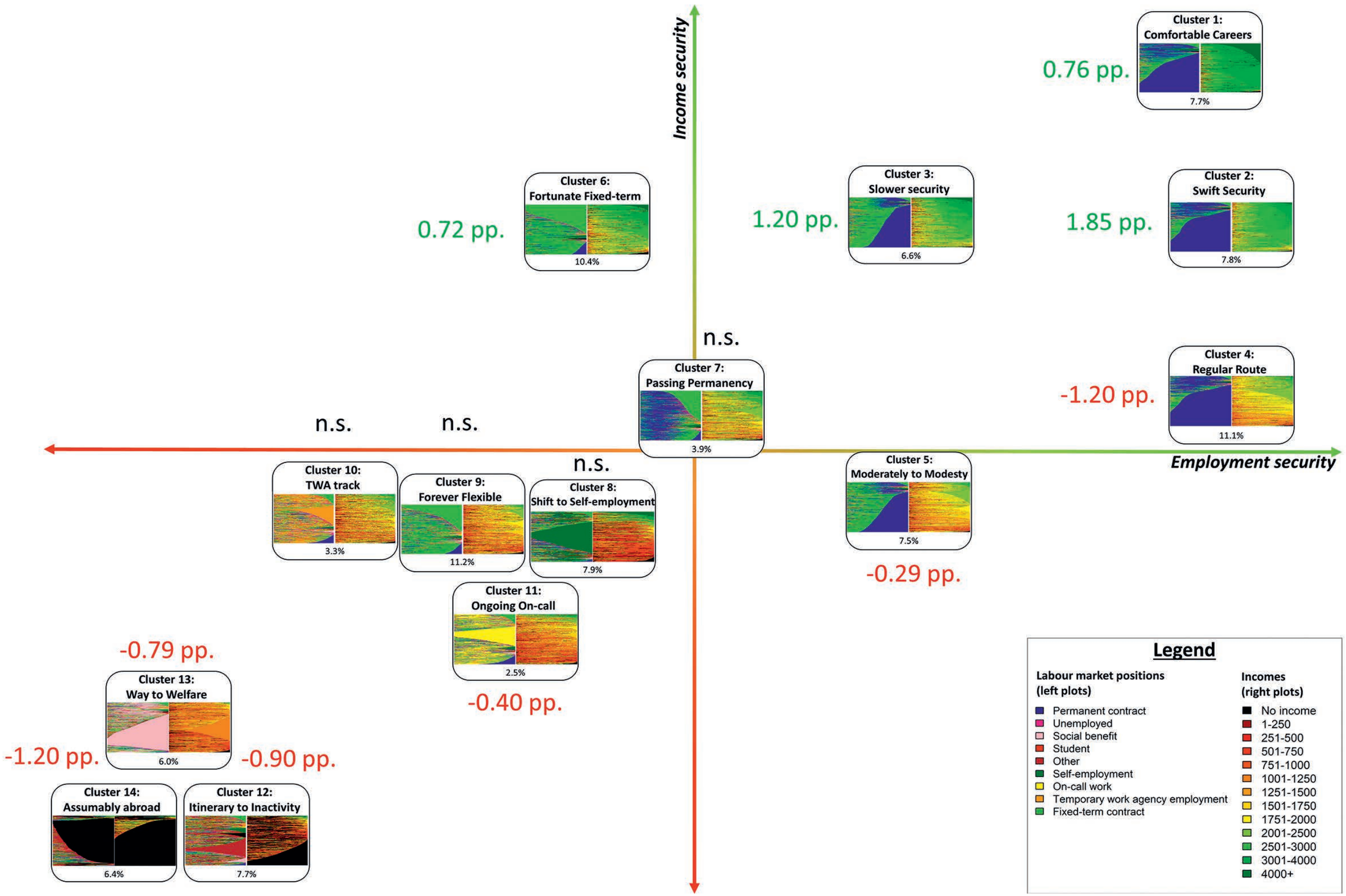


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Table 3.1: Average marginal effects based on multinomial logistic regression on types of school-to-work-transitions[1]

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	Comfortable Careers	Swift Security	Slow Security	Regular Route	Moderately to Modesty	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	TWA track	Ongoing On-call	Itinerary to Inactivity	Way to Welfare	Assumably Abroad
Cluster size	7.72%	7.79%	6.61%	11.10%	7.45%	10.36%	3.86%	7.93%	11.23%	3.32%	2.51%	7.69%	6.04%	6.38%
Specificity (Z)	0.760***	1.851***	1.195***	-1.195***	-0.293**	0.718***	0.145	0.205	-0.232	0.143	-0.402***	-0.897***	-0.794***	-1.204***
	(0.097)	(0.089)	(0.124)	(0.111)	(0.109)	(0.138)	(0.117)	(0.082)	(0.076)	(0.073)	(0.120)	(0.115)	(0.094)	(0.000)
Level of education (ref. ISCED 353 (2y))														
ISCED 353 (3y)	0.946***	0.924***	0.876***	4.564***	2.457***	1.448***	1.604***	1.104***	2.286***	-0.556**	0.271	-3.969***	-11.189***	-0.766***
	(0.140)	(0.138)	(0.126)	(0.296)	(0.262)	(0.166)	(0.162)	(0.233)	(0.329)	(0.180)	(0.206)	(0.329)	(0.439)	(0.215)
ISCED 354	2.222***	5.546***	3.415***	5.779***	2.172***	3.696***	1.394***	1.344***	-1.010**	-1.264***	-0.726**	-6.286***	-14.950***	-1.335***
	(0.190)	(0.228)	(0.196)	(0.324)	(0.271)	(0.220)	(0.168)	(0.255)	(0.342)	(0.198)	(0.212)	(0.358)	(0.498)	(0.218)
ISCED 655	6.849***	11.147***	8.469***	0.259	-1.377***	9.160***	1.293***	1.981***	-7.100***	-2.264***	-1.952***	-8.396***	-19.864***	1.794***
	(0.275)	(0.318)	(0.230)	(0.334)	(0.275)	(0.269)	(0.186)	(0.276)	(0.347)	(0.197)	(0.217)	(0.365)	(0.501)	(0.237)
ISCED 645	11.242***	9.782***	6.125***	-3.823***	-3.434***	7.653***	-0.135	6.667***	-8.762***	-3.406***	-1.825***	-6.124***	-20.752***	6.792***
	(0.765)	(0.947)	(0.702)	(0.633)	(0.534)	(0.763)	(0.383)	(0.841)	(0.694)	(0.231)	(0.380)	(0.528)	(0.517)	(0.442)
ISCED 747/757	18.982***	7.812***	6.681***	-5.540***	-3.546***	14.485***	-0.502**	-1.206***	-10.001***	-3.669***	-2.941***	-7.229***	-21.612***	8.286***
	(0.452)	(0.357)	(0.283)	(0.328)	(0.312)	(0.400)	(0.189)	(0.310)	(0.379)	(0.193)	(0.220)	(0.424)	(0.502)	(0.349)
Cyclical sensitivity (Z)	-0.564***	-0.166	-0.595***	-0.865***	-0.244*	-0.966***	-0.215**	1.507***	-0.004	-0.467***	0.219**	0.498***	0.272*	1.590***
	(0.102)	(0.097)	(0.089)	(0.125)	(0.106)	(0.105)	(0.077)	(0.109)	(0.128)	(0.081)	(0.070)	(0.115)	(0.109)	(0.102)
Specificity * Level of education														
ISCED 353 (2y)	-0.583***	-0.280*	0.384***	-2.625***	0.149	0.945***	0.279*	0.357	2.661***	1.653***	-0.267	-0.861*	-1.435**	-0.376
	(0.118)	(0.115)	(0.087)	(0.300)	(0.240)	(0.121)	(0.123)	(0.217)	(0.317)	(0.157)	(0.227)	(0.365)	(0.532)	(0.204)
ISCED 353 (3y)	0.112	0.291*	0.625***	-1.837***	-0.353	1.066***	0.160	1.484***	0.519	0.727***	-0.590**	-0.657*	-1.241***	-0.305
	(0.109)	(0.114)	(0.106)	(0.285)	(0.251)	(0.146)	(0.154)	(0.204)	(0.313)	(0.154)	(0.205)	(0.274)	(0.334)	(0.172)
ISCED 354	2.327***	5.110***	3.125***	-1.026***	-1.445***	2.672***	0.397*	-1.107***	-3.548***	-0.561**	-1.367***	-1.892***	-2.423***	-0.264
	(0.219)	(0.287)	(0.253)	(0.284)	(0.252)	(0.237)	(0.164)	(0.263)	(0.316)	(0.198)	(0.181)	(0.264)	(0.280)	(0.167)

Table 3.1: *(continued)*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	Comfortable Careers	Swift Security	Slow Security	Regular Route	Moderately to Modesty	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	TWA track	Ongoing On-call	Itinerary to Inactivity	Way to Welfare	Assumably Abroad
Cluster size	7.72%	7.79%	6.61%	11.10%	7.45%	10.36%	3.86%	7.93%	11.23%	3.32%	2.51%	7.69%	6.04%	6.38%
ISCED 655	1.942***	2.177***	0.870***	-0.826***	-0.395**	0.018	-0.165	-0.236	-0.249	-0.560***	-0.044	-0.641***	-0.120	-1.770***
	(0.200)	(0.241)	(0.194)	(0.159)	(0.124)	(0.197)	(0.112)	(0.168)	(0.131)	(0.088)	(0.070)	(0.116)	(0.077)	(0.130)
ISCED 645	-0.928	1.358	0.109	-0.707	0.488	-1.030	-0.118	4.923***	0.619	-0.072	0.393	-0.135	0.116	-5.016***
	(0.719)	(0.884)	(0.670)	(0.490)	(0.473)	(0.667)	(0.345)	(0.875)	(0.557)	(0.193)	(0.332)	(0.438)	(0.183)	(0.454)
ISCED 747/757	-1.270***	1.486***	0.480	0.277	1.473***	-1.257***	0.106	0.018	0.083	-0.160	0.024	-0.767**	-0.148	-0.345
	(0.333)	(0.297)	(0.256)	(0.188)	(0.237)	(0.347)	(0.141)	(0.253)	(0.225)	(0.097)	(0.103)	(0.250)	(0.083)	(0.278)
Specificity * cyclical sensitivity														
Very low	-0.902***	1.714***	1.740***	-1.732***	-0.869***	0.173	0.083	1.495***	-0.250	-1.041***	-0.120	-0.251	-0.975***	0.934***
	(0.215)	(0.158)	(0.155)	(0.268)	(0.216)	(0.237)	(0.153)	(0.122)	(0.249)	(0.243)	(0.103)	(0.188)	(0.198)	(0.109)
Low	-0.164	1.758***	1.411***	-1.510***	-0.619***	0.443**	0.092	0.984***	-0.303	-0.439**	-0.266**	-0.609***	-0.927***	0.149
	(0.127)	(0.104)	(0.097)	(0.161)	(0.135)	(0.140)	(0.096)	(0.102)	(0.166)	(0.129)	(0.077)	(0.136)	(0.136)	(0.091)
Average	0.600***	1.858***	1.177***	-1.209***	-0.304**	0.781***	0.138	0.272*	-0.258	0.077	-0.414***	-0.908***	-0.799***	-1.010***
	(0.092)	(0.098)	(0.094)	(0.125)	(0.112)	(0.112)	(0.076)	(0.112)	(0.140)	(0.082)	(0.074)	(0.119)	(0.115)	(0.088)
High	1.363***	2.017***	1.042***	-0.841***	0.064	1.159***	0.218*	-0.635**	-0.099	0.504***	-0.549***	-1.097***	-0.584***	-2.560***
	(0.121)	(0.140)	(0.131)	(0.169)	(0.155)	(0.151)	(0.103)	(0.191)	(0.196)	(0.092)	(0.121)	(0.179)	(0.163)	(0.174)
Very high	2.097***	2.227***	0.994***	-0.432	0.468*	1.536***	0.325*	-1.685***	0.174	0.843***	-0.654**	-1.144***	-0.285	-4.461***
	(0.167)	(0.191)	(0.168)	(0.226)	(0.212)	(0.198)	(0.137)	(0.338)	(0.278)	(0.119)	(0.194)	(0.277)	(0.240)	(0.348)

[1] Expressed in percentage points. *: p<0.05, **: p<0.01, ***: p<0.001. n=182,057

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The average marginal effects show that, in line with hypothesis 1, specificity on average leads to positive outcomes for school-leavers: the more specific a field of study is, the more likely school-leavers from those fields are to have *Comfortable Careers* (0.76 pp), *Swift Secure* (1.85 pp) or *Slow Secure* (1.20 pp) school-to-work transitions, that offer high levels of employment and income security. At the same time, specificity protects against the most precarious school-to-work transitions, *Itinerary to Inactivity* (-0.90 pp) and *Way to Welfare* (-0.79 pp). Furthermore, specificity decreases the likelihood of having a *Regular Route* (-1.20 pp) and *Moderately to Modesty* (-0.29 pp) school-to-work transitions, that combine relatively good employment security with relatively lower levels of income security, and the likelihood of ending up in an *Ongoing On-call* track (-0.40 pp), that is characterized by long-term precarious on-call employment with low levels of income security. Specificity does increase the probability of having a *Fortunate Fixed-term* school-to-work transition (0.72 pp), which is characterized by long-term fixed-term contracts with high levels of income security. So, when school-leavers from more specific fields of study do end up in flexible employment, these are mostly the non-precarious types of stable flexible employment.

3.4.4. Effects of level of education on school-to-work transitions

In line with human capital theory, there are very large differences between levels of education in the probability of experiencing types of school-to-work transitions. School-leavers with tertiary levels of education are more likely to have *Comfortable Careers* (6.85 to 18.98 pp), *Swift Secure* (7.81 to 11.15 pp) and *Slow Secure* (6.22 to 8.47 pp) school-to-work transitions than graduates from the lowest level of upper-secondary vocational education (ISCED 353, 2 years). These school-to-work transitions are all characterized by high levels of employment and income security. Tertiary levels of education also protect against the most precarious school-to-work transitions that are characterized by non-employment, as well as against school-to-work transitions characterized by low-paid flexible employment, such as *Forever Flexible* (up to -10 pp), *TWA Track* (up to -3.67 pp) and *Ongoing On-call* (up to -2.94 pp). Tertiary levels of education also decrease the probability of experiencing *Regular Route* or *Moderately to Modesty* school-to-work transitions, that combine higher levels of employment security with relatively lower levels of income security (up to -5.54 and -3.55 pp respectively). In contrast, tertiary levels of education increase the probability of *Fortunate Fixed-term* school-to-work transitions, that combine high levels of income security with lower levels of employment security (up to 14.49 pp). All these findings combined, level of education seems to mostly impact the income security of the school-to-work transitions, and only to a lesser extent the employment security.

3.4.5. Effects of cyclical sensitivity on school-to-work transitions

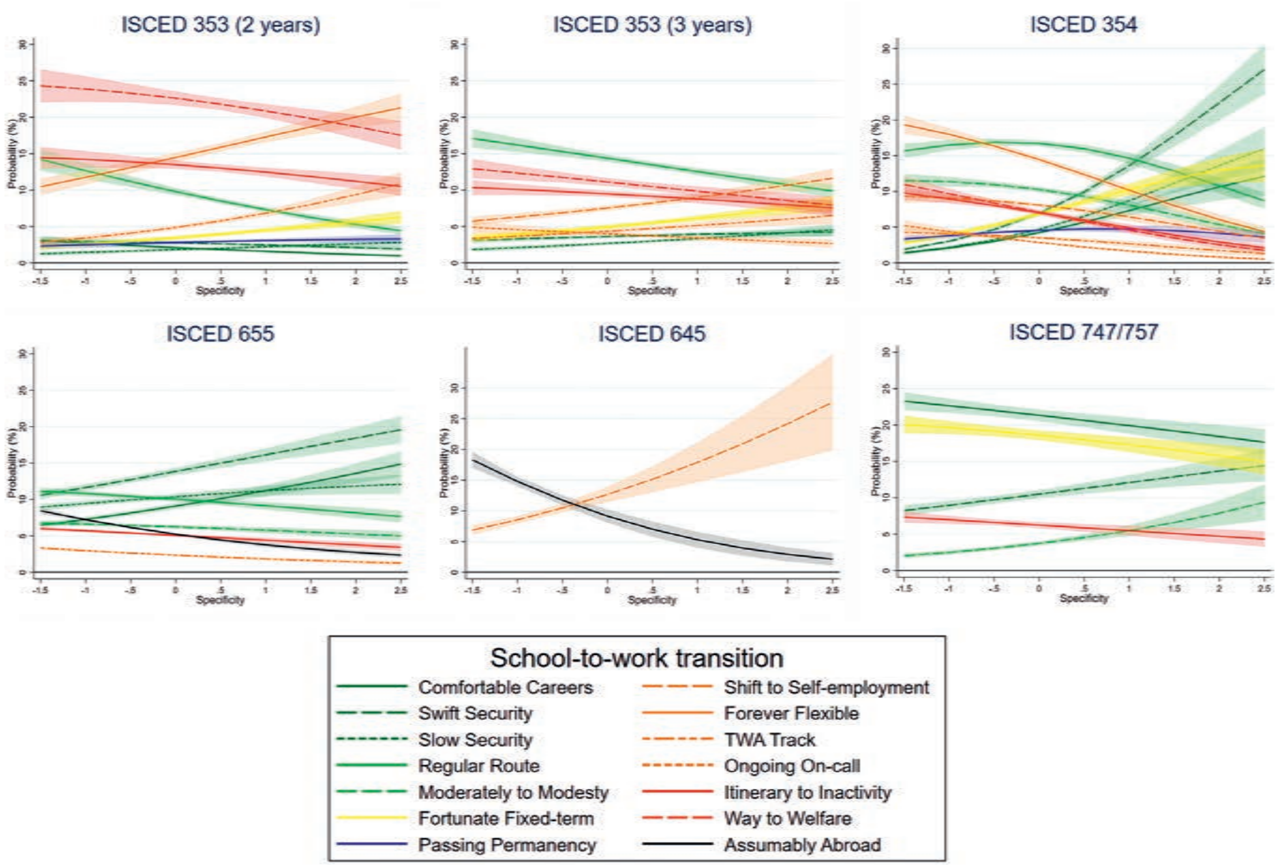
As could be expected in times of economic recession, cyclical sensitivity negatively influences the quality of school-to-work transitions. The more cyclically sensitive a field of study is, the less likely school-leavers from such fields are to experience school-to-work transitions with high levels of employment and income security such as *Comfortable Careers* (-0.56 pp) or *Regular Route* (-0.87 pp). Cyclical sensitivity also strongly increases the probability of making the *Shift to Self-employment* (1.51 pp) or going *Assumably Abroad* (1.59 pp). This indicates that graduates from these fields switch to self-controlled employment or try to seek their luck elsewhere. We furthermore find that cyclical sensitivity slightly increases the likelihood of experiencing school-to-work transitions characterized by non-employment, and to have *Ongoing On-call* school-to-work transitions (0.22 pp). At the same time, school-leavers from more cyclically sensitive fields are less likely to have a *TWA Track* school-to-work transition (-0.47 pp). Cyclical sensitivity has no effect on the probability of experiencing a *Forever Flexible* (-0.00 pp) or *Swift Security* (-0.17 pp) school-to-work transition, indicating that these are common school-to-work transitions regardless of cyclical sensitivity.

2.4.6. The effects of specificity by level of education

The findings confirm hypothesis 2, that expected the effect of specificity to vary across education levels. Specificity is not relevant for all levels of education, and when it is, it is not always an asset for school-leavers. To better grasp the effects of specificity per level of education, we have plotted the significant average marginal effects of specificity on the probability of experiencing the types of school-to-work transitions per level of education (Figure 3.5).

For school-leavers at the lowest level of upper-secondary vocational education (ISCED 353 (2 year) level), specificity increases the probability of school-to-work transitions with intermediate and lower levels of employment security, but protects against non-employment. In more detail, the good news for the school-leavers of this level of education is that specificity protects against the most precarious patterns, *Way to Welfare* (-1.44 pp) and *Itinerary to Inactivity* (-0.86 pp), while it increases the probability of experiencing a *Slow Secure* (0.38 pp) or *Fortunate Fixed-term* (0.95 pp) school-to-work transition, that combine high levels of income security with average levels of employment security. The bad news for this group is that specificity decreases the probability of experiencing the school-to-work transitions with the highest levels of employment security, such as *Comfortable Careers* (-0.58 pp) and *Regular route* (-2.63 pp). It should be noted that the latter pattern is a quite common pattern of school-to-work transitions for school-leavers with this level of education. Also, for this group, specificity increases the probability of having a *Forever Flexible* (2.66 pp) or *TWA Track* (1.65 pp) school-to-work transition.

Figure 3.5: Statistically significant effects of specificity on the probability of experiencing a certain school-to-work transition pattern, per level of education



One level of upper-secondary vocational education higher, at ISCED 353 (3 year), the effects of specificity are more positive compared to the ISCED 353 (2 year) level. In more detail, specificity protects against the most precarious school-to-work transitions characterized by non-employment, as well as against an *Ongoing On-call* (-0.66 pp) school-to-work transition. We now also see that specificity increases the probability of experiencing *Swift* and *Slow Secure* school-to-work transitions (0.29 and 0.63 pp respectively) that offer relatively high levels of employment and income security. Specificity also increases the likelihood of a *Fortunate Fixed-term* school-to-work transition (1.07 pp), that offers relatively high levels of income security for school-leavers at this level of education. However, the picture is not uniformly positive. The fact that specificity increases the probability to follow a *Shift to Self-employment* pattern (1.48 pp) and even more to experience a *TWA track* school-to-work transition (0.73 pp) indicates in some cases that school-leavers with ISCED 353 (3 year) level of education may follow second-best entry patterns into the labour market.

The strongest effects of specificity can be found at the highest level of upper-secondary vocational education (ISCED 354 level). The overall image of these effects is positive for the quality of the school-to-work transitions. Just like at the ISCED 353 levels, specificity decreases the probability of experiencing the most precarious school-to-work transitions characterized by non-employment. We also see that the probability of experiencing school-to-work transitions characterized by precarious employment contracts, such as *Forever Flexible* and *Ongoing On-call*, decreases with the specificity of the field of study. At the same time, specificity increases the probability of experiencing school-to-work transitions characterized by high levels of both employment and income security. This is especially the case for *Swift Secure* school-to-work transitions (5.11 pp): at the lowest level of specificity, school-leavers have only a 1.9% probability of experiencing this school-to-work transition, while this probability is 27.1% at the highest levels of specificity. At the same time, the probability of experiencing a *Regular Route* (-1.03 pp) or a *Moderately to Modesty* (-1.45 pp) school-to-work transition decreases with specificity, and the probability of experiencing a *Fortunate Fixed-term* school-to-work transition increases (2.67 pp). Thus, specificity does not protect against all school-to-work transitions that are dominated by non-standard employment contracts, but those lower levels of employment security are accompanied by high levels of income security.

In bachelor-level tertiary vocational education (ISCED 655), there are fewer and weaker effects of specificity. For instance, specificity does not influence the probability of experiencing *Forever Flexible, Ongoing On-call* and *Shift to Self-employment* school-to-work transitions. It also does not protect against the *Way to Welfare*, which it did for the upper-secondary levels of education. However, the remaining effects of specificity are generally positive: specificity increases the probability of experiencing the school-to-work transitions with the highest levels of employment and income security, and decreases the probability of experiencing an *TWA track* (-0.56 pp) and *Itinerary to Inactivity* (-0.64) school-to-work transition. Specificity also decreases the probability of experiencing *Regular Route*

(-0.83 pp) and *Moderately to Modesty* (-0.40 pp) school-to-work transitions, which have levels of income security that are relatively low for school-leavers at this level of education.

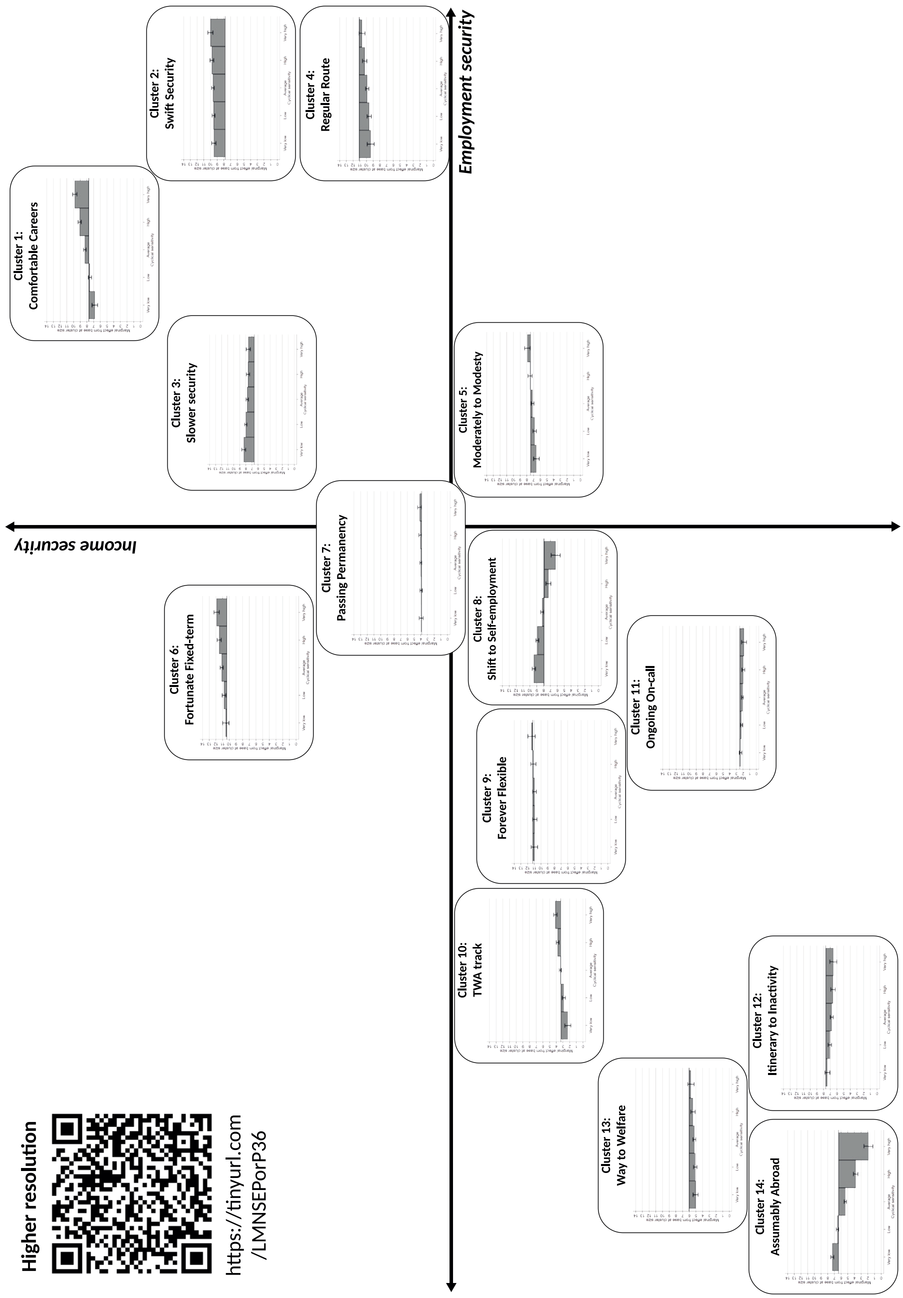
The fewest effects of specificity are found in bachelor-level tertiary academic education (ISCED 645). For these school-leavers, the specificity of the field of study practically does not matter for their probabilities of experiencing any of the school-to-work transitions. The only exceptions are *Shift to Self-employment*, for which specificity strongly increases the probability of experiencing this type of school-to-work transition (4.92 pp), and *Assumably Abroad*, for which specificity strongly decreases the probability (-5.02 pp).

Finally, the effects of specificity are also weak in master-level tertiary education (ISCED 747/757). In the overall, for this group, specificity tends to increase the probability of experiencing school-to-work transitions with lower levels of income security. Again, we observe that specificity does not protect against school-to-work transitions that are characterized by precarious flexible employment, as well as against the *Way to Welfare*. The effects that are significant are also not entirely positive: specificity decreases the probability of experiencing a *Comfortable Career* (-1.27 pp), which has the highest levels of employment and income security. Also, the probability of experiencing a *Fortunate Fixed-term* school-to-work transition decreases with specificity (-1.26 pp). Specificity however does decrease the probability of taking the *Itinerary to Inactivity* (-0.77 pp). At the same time, the probability of experiencing a *Swift Secure* or *Moderately to Modesty* school-to-work transition increases with specificity (1.49 and 1.47 pp). Yet, at this highest level of education, this increased probability of *Moderately to Modesty* is not the best outcome.

3.4.7. The effects of specificity by level of cyclical sensitivity

The effects of specificity do not only differ by level of education, but also by the cyclical sensitivity of the field of study. To illustrate this, we have plotted the marginal effects of specificity for different levels of cyclical sensitivity, relative to the mean cluster size, in Figure 3.6.

Figure 3.6: Marginal effects of specificity per level of cyclical sensitivity, by cluster



Higher resolution

https://tinyurl.com/LMNSEPorP36

3

Our expectation is that, in times of an economic recession, cyclical sensitivity decreases the positive effects of specificity (hypothesis 3). If this expectation was verified then we would expect to see a pattern of a 'descending ladder' in the clusters of the upper-right quadrant (i.e. the relatively prosperous clusters of school-to-work transition) and a pattern of 'ascending ladder' in the bottom-left quadrant (i.e. the relatively precarious clusters). In other words, this would mean that, for the least cyclically sensitive fields of study, specificity increases the probability of following a prosperous school-to-work transition and decreases the probability of following a precarious school-to-work transition.

However, only few results are in accordance with this expectation. In more detail, we see that for highly cyclically sensitive fields of study, specificity increases the probability of experiencing a *TWA Track* school-to-work transition (up to 0.84 pp). For less cyclically sensitive fields of study, specificity rather decreases this probability (up to -1.04 pp). The same holds for *Moderately to Modesty* school-to-work transitions: specificity increases the probability of experiencing this type of school-to-work transition for highly cyclically sensitive fields of study (0.47 pp), but decreases it for less cyclically sensitive fields of study (up to -0.87 pp). Furthermore, we see that specificity decreases the probability of experiencing a *Way to Welfare* school-to-work transition only for less cyclically sensitive fields of study (up to -0.98 pp), while it is irrelevant for the most cyclically sensitive fields of study.

Mostly, Figure 3.6 reveals a direction of the moderating effect of cyclical sensitivity that is against our expectations. We see that for more cyclically sensitive fields of study, specificity strongly increases the probability of having a *Comfortable Career* school-to-work transition, which offers the highest levels of employment and income security (up to 2.10 pp). In contrast, for less cyclically sensitive fields of study, specificity decreases the likelihood of a *Comfortable Career* (up to -0.90 pp). Similarly, we see that for more cyclically sensitive fields of study, specificity decreases the probability of experiencing an *Itinerary to Inactivity* or *Ongoing On-call* school-to-work transition (up to -1.14 pp and -0.65 pp respectively), while these effects are weaker and even non-significant for fields of study that are less or not cyclically sensitive. The opposite holds for *Regular Route* school-to-work transitions: there, specificity decreases the probability of experiencing this type of school-to-work transition for less cyclically sensitive fields of study (up to -1.73 pp), while it does not have an effect for the most cyclically sensitive fields of study. For *Shift to Self-employment* school-to-work transitions, we see that specificity increases the probability of experiencing this type of school-to-work transition for less cyclically sensitive fields of study (up to 1.50 pp), but rather decreases this probability for more cyclically sensitive fields of study (up to -1.69 pp).

As these results contradict our expectations, we did some robustness checks to validate the results and to ensure that the small economic recovery in 2011 had not affected our results. For this purpose, we analysed the effect of specificity and its interplay with cyclical sensitivity on three different employment outcomes measured one, three and six year after leaving education: the probability to be employed, the probability to have a permanent contract, and the mean monthly income. The full results of these robustness checks can be found in Appendix 3D. The robustness checks confirm the direction of the effect of specificity at various levels of cyclical sensitivity: specificity has a positive effect on all three employment outcomes at all three time points for cyclically sensitive fields of study, while having a weaker or even negative effect for cyclically insensitive fields of study.

3.5. Conclusion and discussion

The aim of this chapter was to investigate the effect of the specificity of the field of study on the school-to-work transitions of school-leavers in the Netherlands and how this effect depends on level of education and the cyclical sensitivity of the field of study. Using multichannel sequence analysis, we were able to study school-to-work transitions as processes rather than as single transitions. Furthermore, by studying labour market positions and incomes simultaneously, we were able to assess the quality of school-to-work transitions in terms of both employment security and income security. The multichannel sequence analysis resulted in a typology of 14 school-to-work transitions. By using a continuous scale to measure specificity, we furthermore allowed for more variation in specificity within types of education than the traditional distinction between vocational and general types of education, which resulted in more nuanced insights in the effects of specificity on school-to-work transitions.

The results indicate that horizontal stratification is an important predictor of school-to-work transitions: generally, choosing a more specific field of study results in school-to-work transitions with higher levels of employment and income security. The effect of specificity however depends on vertical stratification – level of education – as well. At the upper-secondary vocational ISCED 354 level of education, specificity has a strong beneficial effect on the quality of school-to-work transitions, while specificity is much less relevant at the tertiary academic levels of education (ISCED 645 and 747/757). This is likely due to the fact that ISCED 354 offers quite high-level skills while having strong connections to employers and therefore prepares for management positions in specific occupations. ISCED 645 and 747/757 levels offer high-level skills as well, but do not have such strong connections with employers, making specificity less beneficial for them. In contrast, education at the upper-secondary vocational ISCED 353 level has strong connections to employers, like ISCED 354, but provides relatively lower-level skills. This has as a consequence that specificity is not very beneficial for members of this group either, though it does protect them against the most precarious school-to-work transitions characterized by non-employment. Finally, specificity was more beneficial for school-leavers at the tertiary vocational ICSED 655 level than expected, though its effect was weaker than at the ISCED 354 level. Though ISCED 655 education is classified as vocational education, just like ISCED 354, the connections between education and employers are much weaker and less formalized than at the upper-secondary levels of education. This could explain why the effect of specificity is weaker at this level of education as well.

The effect of specificity also depended on the cyclical sensitivity of the field of study, but largely contradicted our expectations: several positive effects of specificity were actually stronger for cyclically sensitive fields of study than for cyclically insensitive fields of study. These results go against the expectation that graduates from specific fields of study are less flexible and therefore in a disadvantageous position in economic downturns. However, they are also similar to findings by Blommaert et al. (2020), who also found that specificity is not less, but rather more beneficial in adverse economic contexts. At the same time, we also found that, for some other types of school-to-work transitions, specificity was more beneficial for school-leavers from cyclically insensitive fields of study. These mixed results might be due to the labour market entrance also being affected by the economic circumstances. As stated before, many specific fields of study have incorporated an internship as a structural part of the education program. In economic downturns, students from cyclically sensitive specific fields of study may have more difficulties finding internships - as these become scarce - and therefore experience delays in graduating and entering the labour market. The selective group that is able to find an internship and graduate is then more likely to find employment due to lower supply of graduates. Such effects have been found for Germany, which has a similar coordinated structure as the Netherlands (Muehlemann, Pfeifer, & Wittek, 2020).

Another potential explanation for the weak and negative effects of specificity for cyclically insensitive fields of study is the procyclical policy intervention of the Dutch government in 2011-12 in some economic sectors. In more detail, one would expect that fields of study such as teaching and health care usually remain ignorant of economic crises: the demand for education and health care largely remains the same regardless of the business cycle. However, in response to the economic crisis, the Dutch government chose to implement budget cuts in health care and not to sufficiently compensate for rising costs in education, resulting in lower employment in these sectors after 2011 and 2012 (CBS Statline, 2020b). For school-leavers in these fields, this likely has negatively affected their employment prospects, resulting in a negative effect of specificity for cyclically sensitive fields of study.

Though we have executed this study to the best of our ability, it is not free of limitations. The linkage scale used in this study was the best available way of measuring educational specificity. Yet, it is not perfect. As this scale measures the spread of individuals of a field of study over occupations, it can also pick up on spread caused by lack of employment opportunities in occupations that match with the field of study. For example, in the unlikely situation a sociologist is not able to find matching employment and has to become, for example, a taxi driver, the linkage scale will pick this up as an indication of sociology being a more general field of study. Accounting for the cyclical sensitivity of fields of study will have corrected for this bias somewhat, but we encourage future research to try to filter this cyclical sensitivity out of specificity measures.

Another caveat in this study is that we have excluded school-leavers who entered the labour market, but returned to education at some point. Though we did this to exclude school-leavers who did not make a definitive labour entrance, for instance because they were taking a gap year in between studies, we likely also have excluded individuals who intended to make a definite labour market entrance, but chose to return to education because of low or suboptimal employment prospects. Nevertheless, this is also a very interesting subgroup, and we encourage future research to investigate which factors drive this group to return to education, and whether the return to education pays off.

The new insights provided by this study cannot only function as a stepping stone for future research, but can also inform policy makers who aim to contribute to smoother school-to-work transitions. As the results show the strongest effect of specificity for levels of education with strong connections to the labour market, policy makers could strive to strengthen these education-employer connections for specific fields of study at all levels of education. This is likely to mostly benefit more specific fields of study of tertiary vocational education, where specificity is not as beneficial yet as at the upper-secondary vocational ISCED 354 level. At the same time, the results can be an encouragement for students in and graduates of more general fields of study, especially at tertiary academic levels of education, as a more general field of study at the level may not be as negative for career prospects as they are often led to believe.

Next to the insights in the effects of specificity, we have furthermore shown that a processual approach is an appropriate way to get a detailed image of which types of school-to-work transitions occur, how they fare in terms of employment and income security, and subsequently which factors determine the quality of school-to-work transition in two dimensions. With this approach, we have also gained more insights in the interplay between specificity, level of education and cyclical sensitivity of the field of study on the overall quality of school-to-work transitions. We therefore encourage future research aiming at creating more nuanced insights in school-to-work transitions or other longitudinal phenomena to apply a processual approach.

Appendices to chapter 3

Appendix 3A: The educational system of the Netherlands

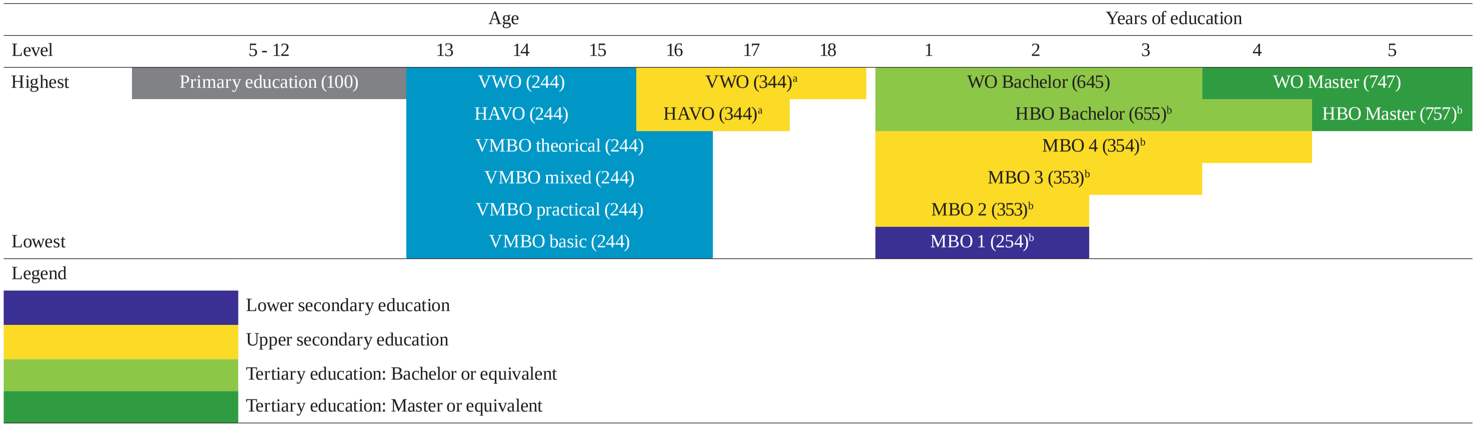
The education system in the Netherlands is highly differentiated and stratified: as soon as in secondary education, students are assigned to a multitude of tracks that vary in level, but to some extent also in field of study (Barone & Van de Werfhorst, 2011). A schematic overview of the education system can be found in Figure 3A.1. Preparatory vocational training already starts at the lower levels of secondary education (VMBO). In VMBO, vocational courses linked to specific fields of work are offered from the early age of 15. They enter post-secondary education at the age of 17. In HAVO and VWO, students receive general education and enter post-secondary education at the age of 16.

At the upper-secondary level, graduates from VMBO enter one of the levels of MBO, in which they specialize in a vocation. Within MBO, a distinction is made between school-based vocational training (MBO-BOL) and work-place based vocational training (MBO-BBL), which resembles the German apprenticeship system. VWO and HAVO students start the second phase of their studies. Their studies as still considered general education, but even here, students have to pick a thematic specialization, which may limit their options in tertiary education. For instance, students who drop courses in biology or chemistry cannot be admitted to tertiary education in Medicine. All these types of education, except MBO 1, provide a labour market starting qualification. However, HAVO and VWO intend to prepare for tertiary education, making labour market entrance after these types of education deviant from the standard path.

At the tertiary level, general, research-oriented education is provided at universities (WO), while vocational education is provided at universities of applied sciences (HBO), in which programs are oriented towards specific occupations (Di Stasio & Van de Werfhorst, 2016). For both types, students start at the bachelor level, which can be followed by a master and even a PhD. However, in the Netherlands, the default is that PhD candidates are employed by the university or research institute. This means that in the context of this research, pursuing a PhD is considered employment and part of the school-to-work transition. Pursuing a PhD is thus not considered as education and individuals obtaining a PhD are not considered to be school-leavers.

Each field of study in MBO, HBO and WO is assigned a nationally standardized code, called CREBO ("*Centraal Register Beroepsopleidingen*", *Central Register Vocational Education*) for MBO and CROHO ("*Centraal Register Opleidingen Hoger Onderwijs*", Central Register Higher Education) for HBO and WO fields of study. These codes are an example of the high levels of standardization in the Netherlands, as the same fields of study at different institutions are assigned the same code. For instance, the bachelor in Sociology in Amsterdam is coded 56601, the same as it is in Nijmegen, Utrecht or elsewhere. As these codes were included in the Education Archives, the types of education enjoyed by our cohort could be easily classified in several educational classifications, such as the ONR2019 (*Opleidingsclassificatie naar Niveau en Richting)*, SOI (*Standaard Onderwijs Indeling)*, and ISCED.

Figure 3A.1: Structure of the education system of the Netherlands



This figure has been largely inspired by the overview of the Dutch education system in Figure A1 in Forster and Bol (2018), as their method of depicting the Dutch education system was difficult to improve. The number in parentheses is the ISCED level code.
[a]: Thematic specialization
[b]: Vocational specialization

Table 3B.1: Number of cases excluded based on selection criteria

	Age <=30	72 months available	Return to education	Full-time education	N
Total sample					278,265
Number of individuals not meeting separate selection criteria	No				55,368
		No			3,651
			Returns to education		20,533
				No	41,079
Number of individuals meeting combinations of selection criteria	No	No	Returns to education	No	60
	No	No	Returns to education	Yes	258
	No	No	Does not return to education	No	51
	No	No	Does not return to education	Yes	130
	No	Yes	Returns to education	No	142
	No	Yes	Returns to education	Yes	468
	No	Yes	Does not return to education	No	19,623
	No	Yes	Does not return to education	Yes	34,636
	Yes	No	Returns to education	No	351
	Yes	No	Returns to education	Yes	1,698
	Yes	No	Does not return to education	No	88
	Yes	No	Does not return to education	Yes	1,015
	Yes	Yes	Returns to education	No	632
	Yes	Yes	Returns to education	Yes	16,924
	Yes	Yes	Does not return to education	No	20,132
Final sample	Yes	Yes	Does not return to education	Yes	182,057
Total number of excluded cases					96,208

Appendix 3B: Selections and Descriptive statistics

Table 3B.2: Descriptive statistics per cluster: employment and income security indicators (means and standard deviations)

Cluster	Comfortable Careers	Swift Security	Slow Security	Regular Route	Moderately to Modesty	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	TWA Track	Ongoing On-call	Itinerary to Inactivity	Way to Welfare	Assumably Abroad	Total
% trajectory in employment	96.93	97.22	96.34	97.43	94.89	92.25	89.73	91.29	90.15	84.71	91.24	37.16	21.98	11.71	79.65
	(6.560)	(6.640)	(6.970)	(6.450)	(8.810)	(10.420)	(11.600)	(10.770)	(12.070)	(12.250)	(10.870)	(23.160)	(20.850)	(18.060)	(30.940)
% trajectory permanent employment	74.06	79.89	47.56	83.19	45.12	7.44	9.38	43.70	5.41	6.59	9.23	4.98	3.23	2.52	32.82
	(22.480)	(18.390)	(15.980)	(17.620)	(19.530)	(10.140)	(12.540)	(18.310)	(10.030)	(10.640)	(14.270)	(10.070)	(8.440)	(8.010)	(35.090)
Duration until permanent employment (months)	11.523	8.422	30.087	7.11	30.343	50.479	45.483	8.361	50.755	52.08	49.909	54.261	59.26	62.698	36.006
	(0.112)	(0.078)	(0.149)	(0.062)	(0.160)	(0.206)	(0.207)	(0.161)	(0.250)	(0.359)	(0.419)	(0.231)	(0.239)	(0.209)	(0.071)
Average within-trajectory income	3007.22	2382.91	2281.65	1842.54	1646.73	2308.96	1464.30	1799.46	1507.80	1497.83	1300.21	1008.85	1134.36	1362.12	1824.36
	(754.190)	(584.740)	(544.290)	(452.120)	(551.510)	(681.240)	(604.200)	(609.840)	(1486.600)	(421.220)	(529.020)	(832.740)	(257.000)	(1461.070)	(931.420)
Standard deviation within-trajectory income	671.93	488.34	541.51	363.39	435.69	612.90	465.75	515.90	699.06	557.00	444.31	475.30	338.49	481.07	508.20
	(450.520)	(317.210)	(290.930)	(241.170)	(288.160)	(404.840)	(388.170)	(328.400)	(763.060)	(190.480)	(208.930)	(654.460)	(207.130)	(1195.330)	(470.970)
Turbulence	4.90	4.53	7.28	4.25	7.81	6.88	9.06	8.96	7.75	11.86	9.21	11.11	7.56	5.32	5.00
N	14,058	14,185	12,032	20,215	13,563	18,857	7,027	14,434	20,452	6,038	4,569	14,002	11,003	11,622	182,057

Table 3B.3: Descriptive statistics per cluster: continuous variables (means and standard deviations)

Cluster	Comfortable Careers	Swift Security	Slow Security	Regular Route	Moderately to Modesty	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	TWA Track	Ongoing On-call	Itinerary to Inactivity	Way to Welfare	Assumably Abroad	Total
Specificity	1.349	1.496	1.478	1.511	1.486	1.561	1.474	1.412	1.553	1.434	1.449	1.360	1.470	1.178	1.454
	(0.628)	(0.653)	(0.701)	(0.578)	(0.598)	(0.820)	(0.627)	(0.635)	(0.664)	(0.644)	(0.570)	(0.577)	(0.555)	(0.599)	(0.652)
Specificity (z)	-0.161	0.064	0.036	0.087	0.049	0.163	0.030	-0.066	0.151	-0.032	-0.009	-0.145	0.024	-0.425	0.000
	(0.963)	(1.003)	(1.076)	(0.886)	(0.917)	(1.258)	(0.962)	(0.975)	(1.019)	(0.989)	(0.875)	(0.885)	(0.852)	(0.918)	(1.000)
Cyclical sensitivity	1.034	1.008	0.984	1.002	1.000	0.980	1.007	1.016	0.992	1.015	0.993	1.006	1.003	1.023	1.003
	(0.133)	(0.140)	(0.138)	(0.107)	(0.108)	(0.150)	(0.114)	(0.124)	(0.113)	(0.094)	(0.103)	(0.097)	(0.089)	(0.109)	(0.120)
Cyclical sensitivity (z)	0.250	0.039	-0.161	-0.009	-0.029	-0.192	0.030	0.101	-0.093	0.096	-0.084	0.023	-0.006	0.160	0.000
	(1.101)	(1.166)	(1.143)	(0.888)	(0.895)	(1.242)	(0.949)	(1.031)	(0.939)	(0.778)	(0.859)	(0.808)	(0.741)	(0.906)	(1.000)
Graduated	0.836	0.823	0.834	0.742	0.663	0.823	0.700	0.503	0.598	0.462	0.539	0.362	0.265	0.650	0.649
	(0.370)	(0.382)	(0.372)	(0.437)	(0.473)	(0.382)	(0.458)	(0.500)	(0.490)	(0.499)	(0.499)	(0.480)	(0.442)	(0.477)	(0.477)
Master medicine	0.011	0.002	0.004	0.001	0.003	0.074	0.002	0.015	0.024	0.000	0.000	0.003	0.001	0.010	0.014
	(0.102)	(0.046)	(0.062)	(0.026)	(0.055)	(0.262)	(0.043)	(0.120)	(0.152)	(0.022)	(0.015)	(0.053)	(0.032)	(0.099)	(0.118)
Small field of study	0.048	0.040	0.035	0.062	0.074	0.038	0.060	0.079	0.085	0.142	0.077	0.124	0.149	0.044	0.072
	(0.214)	(0.197)	(0.184)	(0.241)	(0.263)	(0.192)	(0.238)	(0.269)	(0.278)	(0.349)	(0.266)	(0.33)	(0.356)	(0.205)	(0.258)
Work-based learning	0.155	0.252	0.118	0.414	0.260	0.141	0.331	0.168	0.277	0.317	0.196	0.164	0.263	0.046	0.224
	(0.362)	(0.434)	(0.322)	(0.493)	(0.439)	(0.348)	(0.471)	(0.374)	(0.448)	(0.465)	(0.397)	(0.37)	(0.44)	(0.21)	(0.417)
Age	24.375	23.540	23.064	22.536	21.612	23.589	22.599	21.790	21.354	22.002	21.377	21.725	22.183	23.910	22.599
	(2.705)	(2.752)	(2.489)	(2.904)	(2.635)	(2.580)	(2.947)	(3.154)	(2.717)	(3.051)	(2.746)	(3.129)	(3.26)	(2.842)	(3.004)
N	14,058	14,185	12,032	20,215	13,563	18,857	7,027	14,434	20,452	6,038	4,569	14,002	11,003	11,622	182,057

Table 3B.4: Descriptive statistics per cluster: categorical variables (%)

Cluster	Comfortable Careers	Swift Security	Slow Security	Regular Route	Moderately to Modesty	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	TWA Track	Ongoing On-call	Itinerary to Inactivity	Way to Welfare	Assumably Abroad	Total
N	14,058	14,185	12,032	20,215	13,563	18,857	7,027	14,434	20,452	6,038	4,569	14,002	11,003	11,622	182,057
%	7.72	7.79	6.61	11.10	7.45	10.36	3.86	7.93	11.23	3.32	2.51	7.69	6.04	6.38	100
Level of education															
ISCED 353 (2y) base	4.85	7.28	5.30	13.36	15.84	6.65	13.88	14.22	21.04	31.09	18.54	27.08	39.55	6.86	15.08
ISCED 353 (3y)	8.31	11.02	7.17	25.08	21.80	8.38	21.19	14.60	23.03	19.00	23.24	16.53	21.74	5.01	15.93
ISCED 354 (4y)	8.79	17.42	12.63	28.71	27.42	10.80	21.03	20.20	25.00	17.34	25.15	18.04	18.94	6.75	18.61
ISCED 655	30.52	45.36	53.61	26.96	27.78	38.74	33.46	36.47	22.60	25.64	27.03	23.95	15.43	37.24	31.91
ISCED 645	5.06	3.20	3.30	1.59	1.79	3.61	2.62	6.57	1.89	2.82	2.80	6.23	2.56	11.22	3.89
ISCED 747/757	42.47	15.72	17.99	4.30	5.37	31.81	7.83	7.94	6.44	4.12	3.24	8.18	1.77	32.92	14.58
Field of study															
Teachers	3.40	7.63	12.75	4.84	6.85	7.38	4.58	5.40	7.25	3.96	6.70	5.18	3.67	2.90	6.04
Social sciences & Humanities	11.20	10.50	13.97	7.68	10.06	16.61	11.84	22.53	9.89	10.30	10.18	14.13	9.23	23.83	13.05
Economics & management	28.88	20.08	19.03	18.4	18.02	15.25	19.68	18.09	17.93	23.72	21.78	25.52	21.51	25.12	20.43
Law	8.26	4.42	6.10	3.43	4.48	6.11	3.83	3.76	4.51	7.15	3.50	6.07	5.51	7.10	5.26
Maths & physics	5.99	4.22	4.03	2.70	3.18	4.55	2.97	3.55	2.90	4.69	2.23	5.23	5.77	4.73	4.05
Engineering	24.12	21.71	14.51	17.00	12.26	15.91	19.24	14.84	12.96	24.26	7.38	12.50	11.59	10.70	15.67
Agriculture	2.06	2.48	2.04	3.47	3.01	1.83	3.07	4.95	3.35	3.89	2.74	2.84	3.91	4.06	3.09
Health & Social services	11.60	23.33	20.42	34.46	30.16	24.56	24.38	18.42	27.17	10.43	35.22	19.31	30.36	12.46	23.48
Tourism	4.48	5.63	7.15	8.03	11.99	7.78	10.40	8.46	14.03	11.59	10.29	9.21	8.45	9.10	8.94
Gender															
Male	66.02	54.92	47.49	44.32	42.27	50.77	44.95	51.33	59.04	69.43	38.39	54.11	43.14	44.64	50.44
Female	33.98	45.08	52.51	55.68	57.73	49.23	55.05	48.67	40.96	30.57	61.61	45.89	56.86	55.36	49.56
Migration background															
Native Dutch	82.61	85.15	83.69	85.20	83.89	80.97	82.40	74.77	82.73	67.64	77.19	52.51	62.00	26.76	74.72
Non-western background	9.87	8.97	9.65	9.27	9.96	10.72	10.89	16.74	10.70	24.56	16.44	36.04	30.72	34.62	15.99
Western background	7.51	5.89	6.67	5.54	6.15	8.31	6.72	8.49	6.57	7.80	6.37	11.46	7.28	38.63	9.29

Appendix 3C: Full results

Table 3C.1: Marginal effects based on multinomial logistic regression on types of school-to-work transitions, full results[1]

	Comfortable Careers	Swift Security	Slow Security	Regular Route	Moderately to Modesty	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	TWA Track	Ongoing On-call	Itinerary to Inactivity	Way to Welfare	Assumably Abroad
Specificity	0.760***	1.851***	1.195***	-1.195***	-0.293**	0.718***	0.145	0.205	-0.232	0.143	-0.402***	-0.897***	-0.794***	-1.204***
	(0.097)	(0.089)	(0.124)	(0.111)	(0.109)	(0.138)	(0.117)	(0.082)	(0.076)	(0.073)	(0.120)	(0.115)	(0.094)	(0.000)
Level of education (ref. ISCED 353 (2y))														
ISCED 353 (3y)	0.946***	0.924***	0.876***	4.564***	2.457***	1.448***	1.604***	1.104***	2.286***	-0.556**	0.271	-3.969***	-11.189***	-0.766***
	(0.140)	(0.138)	(0.126)	(0.296)	(0.262)	(0.166)	(0.162)	(0.233)	(0.329)	(0.180)	(0.206)	(0.329)	(0.439)	(0.215)
ISCED 354	2.222***	5.546***	3.415***	5.779***	2.172***	3.696***	1.394***	1.344***	-1.010**	-1.264***	-0.726**	-6.286***	-14.950***	-1.335***
	(0.190)	(0.228)	(0.196)	(0.324)	(0.271)	(0.220)	(0.168)	(0.255)	(0.342)	(0.198)	(0.212)	(0.358)	(0.498)	(0.218)
ISCED 655	6.849***	11.147***	8.469***	0.259	-1.377***	9.160***	1.293***	1.981***	-7.100***	-2.264***	-1.952***	-8.396***	-19.864***	1.794***
	(0.275)	(0.318)	(0.230)	(0.334)	(0.275)	(0.269)	(0.186)	(0.276)	(0.347)	(0.197)	(0.217)	(0.365)	(0.501)	(0.237)
ISCED 645	11.242***	9.782***	6.125***	-3.823***	-3.434***	7.653***	-0.135	6.667***	-8.762***	-3.406***	-1.825***	-6.124***	-20.752***	6.792***
	(0.765)	(0.947)	(0.702)	(0.633)	(0.534)	(0.763)	(0.383)	(0.841)	(0.694)	(0.231)	(0.380)	(0.528)	(0.517)	(0.442)
ISCED 747/757	18.982***	7.812***	6.681***	-5.540***	-3.546***	14.485***	-0.502**	-1.206***	-10.001***	-3.669***	-2.941***	-7.229***	-21.612***	8.286***
	(0.452)	(0.357)	(0.283)	(0.328)	(0.312)	(0.400)	(0.189)	(0.310)	(0.379)	(0.193)	(0.220)	(0.424)	(0.502)	(0.349)
Cyclical sensitivity	-0.564***	-0.166	-0.595***	-0.865***	-0.244*	-0.966***	-0.215**	1.507***	-0.004	-0.467***	0.219**	0.498***	0.272*	1.590***
	(0.102)	(0.097)	(0.089)	(0.125)	(0.106)	(0.105)	(0.077)	(0.109)	(0.128)	(0.081)	(0.070)	(0.115)	(0.109)	(0.102)
Specificity * Level of education														
ISCED 353 (2y)	-0.583***	-0.280*	0.384***	-2.625***	0.149	0.945***	0.279*	0.357	2.661***	1.653***	-0.267	-0.861*	-1.435**	-0.376
	(0.118)	(0.115)	(0.087)	(0.300)	(0.240)	(0.121)	(0.123)	(0.217)	(0.317)	(0.157)	(0.227)	(0.365)	(0.532)	(0.204)
ISCED 353 (3y)	0.112	0.291*	0.625***	-1.837***	-0.353	1.066***	0.160	1.484***	0.519	0.727***	-0.590**	-0.657*	-1.241***	-0.305
	(0.109)	(0.114)	(0.106)	(0.285)	(0.251)	(0.146)	(0.154)	(0.204)	(0.313)	(0.154)	(0.205)	(0.274)	(0.334)	(0.172)
ISCED 354	2.327***	5.110***	3.125***	-1.026***	-1.445***	2.672***	0.397*	-1.107***	-3.548***	-0.561**	-1.367***	-1.892***	-2.423***	-0.264
	(0.219)	(0.287)	(0.253)	(0.284)	(0.252)	(0.237)	(0.164)	(0.263)	(0.316)	(0.198)	(0.181)	(0.264)	(0.280)	(0.167)
ISCED 655	1.942***	2.177***	0.870***	-0.826***	-0.395**	0.018	-0.165	-0.236	-0.249	-0.560***	-0.044	-0.641***	-0.120	-1.770***
	(0.200)	(0.241)	(0.194)	(0.159)	(0.124)	(0.197)	(0.112)	(0.168)	(0.131)	(0.088)	(0.070)	(0.116)	(0.077)	(0.130)
ISCED 645	-0.928	1.358	0.109	-0.707	0.488	-1.030	-0.118	4.923***	0.619	-0.072	0.393	-0.135	0.116	-5.016***
	(0.719)	(0.884)	(0.670)	(0.490)	(0.473)	(0.667)	(0.345)	(0.875)	(0.557)	(0.193)	(0.332)	(0.438)	(0.183)	(0.454)

Table 3C.1: *(continued)*

	Comfortable Careers	Swift Security	Slow Security	Regular Route	Moderately to Modesty	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	TWA Track	Ongoing On-call	Itinerary to Inactivity	Way to Welfare	Assumably Abroad
ISCED 747/757	-1.270***	1.486***	0.480	0.277	1.473***	-1.257***	0.106	0.018	0.083	-0.160	0.024	-0.767**	-0.148	-0.345
	(0.333)	(0.297)	(0.256)	(0.188)	(0.237)	(0.347)	(0.141)	(0.253)	(0.225)	(0.097)	(0.103)	(0.250)	(0.083)	(0.278)
Specificity * Cyclical sensitivity														
Very low	-0.902***	1.714***	1.740***	-1.732***	-0.869***	0.173	0.083	1.495***	-0.250	-1.041***	-0.120	-0.251	-0.975***	0.934***
	(0.215)	(0.158)	(0.155)	(0.268)	(0.216)	(0.237)	(0.153)	(0.122)	(0.249)	(0.243)	(0.103)	(0.188)	(0.198)	(0.109)
Low	-0.164	1.758***	1.411***	-1.510***	-0.619***	0.443**	0.092	0.984***	-0.303	-0.439**	-0.266**	-0.609***	-0.927***	0.149
	(0.127)	(0.104)	(0.097)	(0.161)	(0.135)	(0.140)	(0.096)	(0.102)	(0.166)	(0.129)	(0.077)	(0.136)	(0.136)	(0.091)
Average	0.600***	1.858***	1.177***	-1.209***	-0.304**	0.781***	0.138	0.272*	-0.258	0.077	-0.414***	-0.908***	-0.799***	-1.010***
	(0.092)	(0.098)	(0.094)	(0.125)	(0.112)	(0.112)	(0.076)	(0.112)	(0.140)	(0.082)	(0.074)	(0.119)	(0.115)	(0.088)
High	1.363***	2.017***	1.042***	-0.841***	0.064	1.159***	0.218*	-0.635**	-0.099	0.504***	-0.549***	-1.097***	-0.584***	-2.560***
	(0.121)	(0.140)	(0.131)	(0.169)	(0.155)	(0.151)	(0.103)	(0.191)	(0.196)	(0.092)	(0.121)	(0.179)	(0.163)	(0.174)
Very high	2.097***	2.227***	0.994***	-0.432	0.468*	1.536***	0.325*	-1.685***	0.174	0.843***	-0.654**	-1.144***	-0.285	-4.461***
	(0.167)	(0.191)	(0.168)	(0.226)	(0.212)	(0.198)	(0.137)	(0.338)	(0.278)	(0.119)	(0.194)	(0.277)	(0.240)	(0.348)
Field of study (ref. Technical studies)														
Agricultural sciences	-6.558***	-4.396***	-3.203***	-0.199	0.653	-5.319***	-0.649*	5.626***	2.692***	-0.173	0.908***	1.762***	3.396***	5.460***
	(0.407)	(0.393)	(0.356)	(0.431)	(0.347)	(0.432)	(0.272)	(0.476)	(0.441)	(0.276)	(0.211)	(0.427)	(0.387)	(0.489)
Catering and tourism	-6.170***	-4.970***	-1.610***	-2.350***	2.726***	-0.950*	-0.072	0.504	6.966***	-0.449*	1.397***	1.152***	0.692**	3.136***
	(0.342)	(0.300)	(0.298)	(0.287)	(0.259)	(0.377)	(0.204)	(0.259)	(0.324)	(0.184)	(0.147)	(0.269)	(0.215)	(0.318)
Economics and business	-1.195***	-1.309***	-0.554*	-1.260***	0.947***	-3.614***	-0.155	0.985***	2.247***	-0.158	1.233***	1.558***	0.981***	0.294
	(0.308)	(0.296)	(0.268)	(0.286)	(0.233)	(0.303)	(0.192)	(0.245)	(0.286)	(0.189)	(0.134)	(0.252)	(0.219)	(0.228)
Health care	-6.957***	-2.826***	-2.209***	4.035***	3.184***	-2.125***	-0.106	0.538*	2.989***	-1.752***	2.214***	1.027***	2.604***	-0.616*
	(0.311)	(0.296)	(0.266)	(0.302)	(0.234)	(0.330)	(0.187)	(0.234)	(0.263)	(0.159)	(0.133)	(0.236)	(0.201)	(0.240)
Humanities and social sciences	-8.706***	-5.270***	-2.186***	-1.188***	1.995***	-2.720***	-0.068	6.922***	4.636***	0.148	1.134***	2.272***	3.241***	-0.211
	(0.272)	(0.270)	(0.256)	(0.321)	(0.271)	(0.309)	(0.206)	(0.304)	(0.346)	(0.217)	(0.145)	(0.270)	(0.285)	(0.212)
Legal studies	-4.446***	-3.711***	0.249	1.797***	2.605***	-1.648***	-0.468	-0.565	3.288***	-0.121	0.858***	1.291***	1.710***	-0.840**
	(0.342)	(0.364)	(0.375)	(0.497)	(0.378)	(0.396)	(0.264)	(0.312)	(0.414)	(0.224)	(0.192)	(0.312)	(0.281)	(0.255)

Table 3C.1: *(continued)*

	Comfortable Careers	Swift Security	Slow Security	Regular Route	Moderately to Modesty	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	TWA Track	Ongoing On-call	Itinerary to Inactivity	Way to Welfare	Assumably Abroad
Maths and natural sciences	-4.312***	-2.845***	-0.652	0.600	1.740***	0.031	-0.513	-1.704***	2.170***	0.310	0.155	1.146**	4.097***	-0.223
	(0.348)	(0.373)	(0.369)	(0.490)	(0.386)	(0.451)	(0.281)	(0.268)	(0.452)	(0.291)	(0.163)	(0.338)	(0.385)	(0.286)
Teaching	-8.314***	-3.864***	0.086	-1.281**	2.988***	-1.795***	-1.341***	1.495***	8.054***	-1.124***	1.785***	2.572***	1.130***	-0.390
	(0.355)	(0.365)	(0.366)	(0.393)	(0.358)	(0.436)	(0.231)	(0.368)	(0.482)	(0.240)	(0.213)	(0.396)	(0.315)	(0.362)
Graduated	3.851***	4.661***	4.319***	4.409***	0.760***	4.967***	0.780***	-3.918***	-1.446***	-1.571***	-0.856***	-6.854***	-8.172***	-0.931***
	(0.131)	(0.128)	(0.119)	(0.152)	(0.137)	(0.154)	(0.100)	(0.154)	(0.168)	(0.097)	(0.087)	(0.155)	(0.134)	(0.130)
Master Medicine	-2.433**	-7.529***	-6.109***	-10.628***	-6.744***	16.862***	-3.420***	2.634	29.504***	-1.396	-2.469***	-4.266***	1.892	-5.898***
	(0.854)	(0.146)	(0.177)	(0.217)	(0.253)	(2.830)	(0.198)	(2.242)	(4.840)	(1.304)	(0.073)	(0.926)	(3.397)	(0.201)
Too small	1.834***	1.241**	1.101*	-2.717***	-0.999**	2.397***	-0.083	0.717	-1.404***	1.950***	-0.797***	-0.989***	-0.766**	-1.484***
	(0.418)	(0.466)	(0.445)	(0.351)	(0.309)	(0.540)	(0.263)	(0.388)	(0.365)	(0.288)	(0.153)	(0.275)	(0.237)	(0.277)
Dual system	3.260***	8.072***	-0.360	7.994***	-0.777***	0.377	1.439***	-2.940***	-1.957***	-1.127***	-1.190***	-4.767***	-3.958***	-4.066***
	(0.360)	(0.395)	(0.249)	(0.268)	(0.169)	(0.310)	(0.164)	(0.173)	(0.195)	(0.110)	(0.085)	(0.140)	(0.123)	(0.150)
Gender	-3.055***	-1.217***	-0.239	1.538***	1.502***	-1.421***	0.065	-2.616***	2.201***	-1.317***	0.593***	-0.179	2.862***	1.281***
	(0.134)	(0.149)	(0.135)	(0.177)	(0.146)	(0.161)	(0.110)	(0.144)	(0.173)	(0.094)	(0.085)	(0.138)	(0.129)	(0.115)
Age	0.721***	0.445***	-0.176***	0.339***	-0.436***	0.185***	0.088***	-0.737***	-0.827***	0.081***	-0.137***	-0.307***	0.703***	0.059**
	(0.024)	(0.024)	(0.025)	(0.027)	(0.027)	(0.029)	(0.017)	(0.027)	(0.032)	(0.016)	(0.016)	(0.024)	(0.019)	(0.021)
Migration background														
Non-western background	-3.567***	-3.058***	-1.783***	-4.356***	-2.957***	-2.245***	-1.133***	1.035***	-4.190***	1.142***	-0.201	8.114***	1.089***	12.108***
	(0.154)	(0.170)	(0.169)	(0.193)	(0.161)	(0.203)	(0.124)	(0.196)	(0.192)	(0.128)	(0.104)	(0.211)	(0.142)	(0.220)
Western Background	-3.756***	-3.407***	-2.312***	-3.520***	-1.927***	-2.408***	-0.933***	-0.244	-2.190***	0.059	-0.514***	4.173***	-0.490*	17.469***
	(0.166)	(0.189)	(0.179)	(0.252)	(0.220)	(0.222)	(0.157)	(0.223)	(0.269)	(0.153)	(0.131)	(0.242)	(0.190)	(0.275)

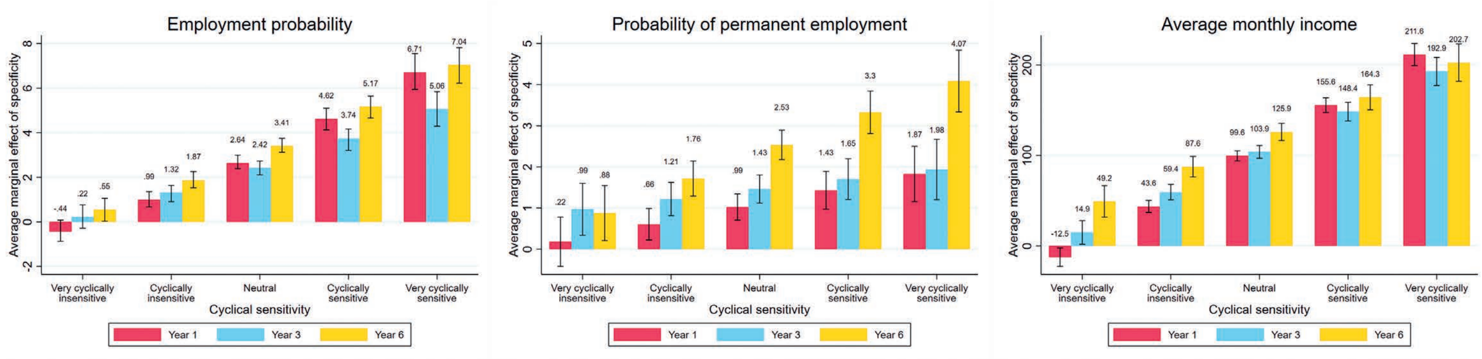
[1] Expressed in percentage points. *: p<0.05, **: p<0.01, ***: p<0.001. N=182,057

Appendix 3D: Robustness checks

During the six years of the school-to-work transition we studied, the economic conditions varied over time. For that reason, the interaction between specificity and cyclical dependency might have changed over time as well. To test the robustness of our findings, we also evaluated the interaction between specificity and cyclical sensitivity separately at one three and six years after leaving education. We used three outcomes: employment probability (including all types of (non-standard) employment, probability of permanent employment and the average monthly income earned in that year. In the analysis, we included all variables and interactions that are also included in the original multinomial logistic regression with the typology of school-to-work transitions as the dependent variable (see section 4.2). The results of the robustness checks are plotted in Figure 3D.1. Figure 3D.1 shows the average marginal effects of specificity per level of cyclical sensitivity and per year after leaving education.

We see that, in general, specificity has a stronger effect for cyclically sensitive fields of study than for cyclically insensitive fields of study. In the latter group, we often see that specificity in the short term often has no effect, or even a small negative effect in the case of average monthly income. The only exception to this rule is the probability of permanent employment after 3 years, where the effect of specificity does not significantly differ per level of cyclical sensitivity, though the trend goes in the same direction. All in all, these robustness checks confirm the found interactions effects between specificity and cyclical sensitivity found with the original multinomial logistic regression.

Figure 3D.1: Average marginal effects of specificity per level of cyclical sensitivity on employment probability, permanent employment probability and average monthly income after 1, 3 and 6 years.



4

Occupations and the non-standard employment career

How the occupational skill level and task types influence the career outcomes of non-standard employment

Abstract

This chapter examines to what extent the occupational skill level and task types determine whether non-standard employment leads to a stepping stone or a trap in the careers of workers. For this purpose, a typology of the individual careers of workers in the Netherlands who entered non-standard employment in 2007 is created using multichannel sequence analysis. This typology allows for classifying careers in terms of employment security and income security. An analysis of this typology shows that working in occupations with high-level tasks does not preclude trap careers with low levels of employment and income security. Routine tasks do not have an unequivocal effect on career outcomes, while manual tasks generally lead to trap careers. The combination of routine and manual tasks makes it most likely for non-standard employment to function as a trap in workers' careers.

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4.1. Introduction

Non-standard employment contracts – i.e. fixed-term contracts, on-call contracts or temporary agency contracts – are becoming increasingly popular in contemporary labour markets. In the Netherlands, the share of workers with such contracts has soared from 16.1% in 2003 to 26.9% in 2018 (CBS Statline, 2019). The flexibility that these contracts offer is highly valued by employers and policy makers. However, simultaneously, severe concerns have been raised about the consequences of these contracts on workers' well-being. Since there is consensus that these types of contracts are, at a given point in time, ceteris paribus, inferior to permanent contracts with respect to employment security, earnings, fringe benefits, training and promotion (Booth et al., 2002; De Beer, 2016; OECD, 2014), research has shifted its focus to the career effects of non-standard employment. The scientific debate that dominates the field is whether non-standard employment functions as a *stepping stone* to well-paid and more stable types of employment, or as a *trap* of repeated low-paid non-standard jobs or unemployment (Berton et al., 2011; De Graaf-Zijl et al., 2011; Giesecke & Groß, 2003). However, the answers that previous research has provided on this debate are incomplete as they are limited to the effect of supply side factors: how individual characteristics, such as gender and education, determine the effect of non-standard employment in the employment career (Booth et al., 2002; Gash & McGinnity, 2007). Although the organisation is the key level where the employment relationship is determined (Tomlinson, Baird, Berg, & Cooper, 2018), the effect of demand-side factors has remained largely overlooked until now.

In sociology, occupation has been considered as a factor that summarizes demand-side factors of employment. Specifically, for non-standard employment, occupational characteristics influence the necessity of long-term employer-employee commitment and consequently the careers of the workers in these occupations (Goldthorpe, 2007; Van Echtelt et al., 2015). However, only a handful number of studies focus on how occupations affect the role of non-standard employment in the career (Kiersztyn, 2016; Polavieja, 2005; Reichelt, 2015). Moreover, both the scope of these studies and their operationalization of career effects are limited. In more detail, the scope of these studies is restricted to studying a single aspect of occupations, being the *skill level*, while neglecting other important occupational characteristics. As Acemoglu and Autor (2011) and Goldthorpe (2007) suggest, the *types of tasks* executed in the occupation are also crucial in determining career dynamics. Furthermore, the operationalization of the *career effects* of non-standard employment in existing studies is incomplete because they only study point-in-time transitions from non-standard to permanent employment, and in this way neglect career-dynamics both before and after this transition.

The aim of this chapter is to address the shortcomings mentioned above by introducing two innovations. The first is that the extent to which both the occupational skill level and the types of tasks executed in the occupation determine whether non-standard employment leads to a successful or a precarious career is investigated. The second is that, instead of defining career outcomes as single events as previous research has done, a processual approach in which employment trajectories are treated as the unit of analysis is adopted. In this processual approach, two dimensions of career quality are studied simultaneously: employment security and income security. These two innovations are achieved by using multichannel sequence analysis on a unique Dutch register dataset that allows for following workers that entered non-standard employment in 2007 on a monthly basis for an eight-year period.

4.2. Theoretical framework

4.2.1. Non-standard employment: a stepping stone or a trap?

The sociological and economic literature identifies two opposing scenarios on the effect of non-standard employment on the career. The *stepping stone* scenario has its roots in human capital theory and suggests that working with a non-standard employment contract improves career prospects in comparison to remaining unemployed as workers acquire skills, work experience and social capital (Booth et al., 2002; De Graaf-Zijl et al., 2011; Giesecke & Groß, 2004). This is corroborated by the signalling-screening perspective (Spence, 1973), which suggests that employers use non-standard employment as an extended probation period to screen the productivity of new hires. In this way, workers who meet the employer’s expectations are later offered a permanent contract (Booth et al., 2002; Weiss, 1995).

The arguments of the *trap* scenario are mainly based on dual labour market theory (Doeringer & Piore, 1971; Hudson, 2007). The main argument is that employers mostly use non-standard employment as a means to adapt the workforce to economic fluctuations (Kalleberg, 2003). Therefore, employers are less likely to invest in the human capital of workers with such contracts. From a signalling-scarring perspective, this can have long-term negative effects on the career of workers as future employers consider an employment history containing non-standard employment as a signal of lower worker quality (Berton et al., 2011; Hudson, 2007).

Most research has largely focused on determining *which* of both scenarios holds. However, these studies adopt an approach that does not correspond to reality in contemporary labour markets. Firstly, most studies focus on point-in-time transitions from non-standard to permanent employment (e.g. Gash, 2008; Reichelt, 2015). This approach is appropriate when linear career pathways leading from non-standard to permanent employment are dominant in the labour market, but less suitable for contemporary labour markets where lifelong jobs are becoming less standard. Secondly, research generally studies employment and income outcomes separately (Booth et al., 2002; De Graaf-Zijl et al., 2011). However, in contemporary labour markets, individuals trade different types of security by e.g. choosing a high-paid temporary job instead of a permanent job with lower earnings or vice versa. Mattijssen and Pavlopoulos (2019) argue that the outcomes of non-standard employment can best be assessed by adopting a processual approach and treating employment and income trajectories as the unit of analysis, as this leads to a much more complete picture where career quality is assessed on the basis of two dimensions: *employment security* – the types of (non-standard) employment encountered in the career, the number of changes between labour market positions, and the time spent in non-employment –, and *income security* – the income level, growth and stability.

Nevertheless, as the results of previous studies suggest that both the stepping stone and trap scenario are plausible, the question is not as much *which* of both scenarios holds, but *when* and *for whom* the scenarios hold. Therefore, the same approach as Mattijssen and Pavlopoulos (2019) will be used, also focusing on the dimensions of employment and income security, to determine to what extent the skill level and task content of occupations play a role in determining the career outcomes.

4.2.2. The effect of occupations on career quality

In research aiming to explain when non-standard employment leads to positive (i.e. stepping stone scenario) or negative outcomes (i.e. trap scenario), the focus lies disproportionally on supply-side factors, such as gender and education. However, whether non-standard employment has positive or negative outcomes in the career is predominantly determined by employer motives. In more detail, employers use non-standard contracts as a means to obtain greater flexibility or as a screening device for new hires (Kalleberg, 2003). The former motive probably results in a short-term employment relationship, whereas the latter implies a necessity for long-term employer-employee commitment. When such a necessity exists, employers have an incentive to convert the non-standard contract to a permanent contract after successful screening. In this case, a non-standard contract functions as a stepping stone in the career of the worker (Berglund et al., 2017; Houseman, 2001). In contrast, when the necessity for a long-term commitment is absent, the trap-scenario for the career is more plausible.

Employer motives – i.e. whether they use non-standard employment for screening or flexibility – is driven by the replaceability of the worker. In more detail, if the worker is easily replaceable, then the employer will have no incentive to use long-term employment relationships and will use non-standard employment contracts as a means to accommodate economic fluctuations. However, if the worker is not easily replaceable, the employer has an incentive to engage the worker in a long-term employment relationship. In this case, the employer will use an non-standard employment contract mostly as a screening device for suitable candidates. The replaceability of workers is closely linked to their occupations and specifically to the tasks that are inherent in these occupations. In research, two aspects of occupational tasks have been recognized as determinants of replaceability and therefore of the career outcomes of non-standard employment: the skill level and the type of tasks executed in the occupation.

4.2.3. Skill level

In the discussion of occupational stratification, Parsons argued that the requirement of rare abilities and competences that can only be acquired by training make differentiation inherent in occupations (Parsons, 1949, p. 20). Obviously, this means that the level of education of the individual is an important determinant of career outcomes, which is confirmed by numerous studies (e.g. Booth et al., 2002; Giesecke and Groß, 2003). However, irrespectively of the education level, the skill level of the tasks executed in an occupation is relevant as well, as this mainly determines the necessity of long-term employer-employee commitment (Lepak & Snell, 1999). Specifically, in occupations that involve high-level tasks, suitable candidates for the job are scarce (Reichelt, 2015). This motivates employers to establish long-term employment relationships with suitable candidates as replacing them is difficult. In these occupations, non-standard contracts are mostly used as a screening device to ensure that the workers are able to perform the high-level tasks adequately. This results in higher levels of employment security for workers in these occupations, as they are more likely to have stable employment and to make the transition to permanent employment.

In contrast, vacancies for jobs in occupations with low-skilled tasks are easier to fill as more job seekers meet the job requirements, making these workers more replaceable. In these jobs, long-term commitment is much less needed and employers hire workers in non-standard contracts for the purpose of adapting their workforce to economic fluctuations. This will make it less likely that a non-standard contract is converted to a permanent contract in low-skilled occupations (Kiersztyn, 2016; Reichelt, 2015), which would result in careers consisting of spells of unstable non-standard employment and even unemployment. In this respect, the skill level of occupational tasks is a more crucial determinant of employers' motives for using non-standard employment than the educational level of the individual workers: if a high-skilled individual is hired in a low-skilled job, the employer still does not require long-term commitment and has no reason to offer the high-skilled worker employment security.

With respect to income, workers acquire the skills required for the occupation through education and training. Therefore, according to human capital theory, workers will be compensated for these efforts with higher wages (Mincer, 1974). To summarize, the mechanisms discussed above indicate that *workers who enter non-standard employment in occupations with high-skilled tasks have careers with more stable employment, with fewer non-standard employment contracts and less unemployment (i.e. more employment security), as well as higher and more increasing incomes (i.e. more income security) than workers in occupations with low-skilled tasks (H1*).

4.2.4. Task types

Apart from the skill level of the tasks performed in occupations, Autor, Levy and Murnane (2003) suggest that the types of tasks executed in an occupation are crucial in explaining employment outcomes. Their main argument is that the types of tasks executed in occupations determine the extent to which workers are replaceable and consequently how susceptible occupations are to automation.

Their argument can be connected to Goldthorpe's (2007) framework, as task types can directly be linked to two broader characteristics of occupations that strongly influence the replaceability of the worker and subsequently the possibility that an initial non-standard contract is converted to a permanent contract: the extent to which workers can be *monitored* while performing their tasks and the extent to which *specific skills* are required in order to fulfil these tasks. When monitoring costs are high, employers use incentives, such as a permanent contract (Goldthorpe, 2007) or an efficiency-wage premium (Akerlof & Yellen, 1986), to prevent the worker from shirking. In contrast, when monitoring costs are low, such incentives are unnecessary. Similarly, when specific skills are required for the job, employers seek a long-term commitment with high wages, as investments in the firm-specific skills of workers are costly (Lazear, 1995). Therefore, both the existence of high monitoring costs and the specificity of skills in a job reduce the replaceability of the worker and lead to the necessity of long-term employment relationships. Subsequently, high monitoring costs and high levels of skill specificity lead employers to use an initial non-standard contract as a screening device for new hires, resulting in stepping stone careers with high levels of employment security.

Monitoring costs and skill specificity are difficult to observe. However, they are jointly represented in a specific aspect of occupational task types: routine. Routine tasks can easily be expressed in a set of rules (Autor et al., 2003), which makes them easy to monitor and easy to execute without requiring specific skills. This would mean that workers in occupations that consist mostly of routine tasks are more likely to have a career with low levels of employment security: providing them with incentives is not necessary, as they can be easily monitored, while they can also be replaced easily, both by other workers and automation, as their job requires few specific skills.

Though routine tasks are likely to affect employment security, their relationship with income security is much less evident. Autor and Handel (2013) suggest that routine tasks were the least stable predictor of wages and show that another aspect of tasks is important for income: whether the tasks are manual. In accordance to this, Fouarge et al. (2017) find that manual tasks are more prevalent in the lower income quintiles, while non-manual tasks are more common in the higher income quintiles. Confirming the consideration of Autor and Handel that the level of manual tasks in an occupation is more important than routine, they also find that routine manual tasks are mostly found in the second lowest income quintile, while routine cognitive tasks are equally common in the lower four quintiles. Therefore, it is expected that *the careers of workers in routine occupations are less stable in terms of employment, with more non-standard employment contracts and unemployment spells (i.e. lower levels of employment security), than the careers of workers in non-routine occupations, irrespective of income security (H2a)*, while *workers in manual occupations are more likely to have lower and more unstable incomes (i.e. lower levels of income security), irrespective of employment security (H2b).*

4.3. Data and methodology

In this chapter, a unique Dutch dataset that links individual-level information from register and survey data was used. Longitudinal information on employment and income came from the *System of social statistical datasets (SSD*) from Statistics Netherlands. The SSD contains information for all workers in the Netherlands, from the Dutch tax administration ('de Belastingdienst'), the register on wages ('Polisadministratie') and the Employee Insurance Agency ('UWV') (Bakker et al., 2014). A subset of this dataset, which was created specifically for the purpose of studying careers of workers who entered non-standard employment, was used. These data offered exact information, including start and end dates, on the employment status, contract type, income and income sources of individuals aged between 15 and 74 from the moment they entered non-standard employment in 2007 until December 2015 (De Vries et al., 2017). For the analysis, workers who entered non-standard employment between January 1st and December 31st 2007 were selected. These individuals were followed until December 2015, which allowed for studying every individual for 96 months. The information on income included income from paid employment, self-employment and income from benefits.

As the focus lies on career development, student side-jobs were filtered out by only selecting workers who were not enrolled in education at the moment they entered non-standard employment. If someone re-entered non-standard employment in 2007 after leaving education, that job was included as the first job. The age range was restricted to exclude individuals aged under the compulsory schooling age of 18 and workers aged over 60 as they reach the retirement age before the end of the observation period. Workers whose main income was a pension benefit for more than 12 months of the observation period were excluded from the sample as well.

Information on occupation at the time of the entry in non-standard employment as well as additional information on individual characteristics was derived from the Dutch Labour Force Survey (LFS). The LFS is a rotating panel survey that aims at monitoring the Dutch labour market. Respondents are surveyed five times, with an interval of three months between surveys. Each trimester, around 0.9% of the households is randomly selected into the sample. The two data sources were linked at the individual level on the basis of the first job of the observation period in the register data: information from the first LFS observation that occurred after entering non-standard employment was linked to the register data. In this stage, 1% of the register-data observations could be linked to information from the LFS (N=6,865).

Linkage between the LFS and the register data revealed some inconsistencies. Sometimes, individuals reported in LFS that they did not have a job whereas in the register data they were registered as employed. This resulted in missing occupations. Taking the information from the register data as leading, this problem was partly solved by extrapolating the first available information about the individual's occupation from other LFS waves. Despite this correction, for 9.2% of the linked cases information on the occupation remained missing and therefore these cases were excluded from the analysis.[13] After also excluding cases listwise, the sample consisted of 6,004 workers.

4.3.1. Dependent variable

The dependent variable for the analysis is the typology of non-standard employment careers. This typology was constructed with multichannel sequence analysis, taking

13 Occupation was missing not at random. It turned out that individuals whose occupation was unknown were overrepresented in a couple of the more precarious clusters of the typology that is discussed in section 4. As individuals with missing values on occupation were excluded from the analysis, these clusters are underrepresented in the typology. A representative image of the Dutch labour market can be found in Mattijssen and Pavlopoulos (2019).

labour market positions and income as its two ‘channels’. Multichannel sequence analysis is a statistical method that allows for describing multiple series of states that subsequently can be classified in terms of similarity (Cornwell, 2015; Pollock, 2007). Producing a typology that is representative for the population is an inherent problem in sequence analysis, especially when sequences are very heterogeneous, as is the case in this chapter. Therefore, the typology was built using the representative (‘medoid’) sequences of the typology that was produced by Mattijssen and Pavlopoulos (2019). This typology was created using the same register data and was based on a much larger sample of exactly the same population. The representativeness of this typology was established with a replication strategy. The multichannel sequence analysis was conducted in the statistical software R (R Core Team, 2019) using the TraMineR package (Gabadinho, Ritschard, Studer, et al., 2011). More details about this procedure can be found in Appendix 4A.

4.3.2. Independent variables

The two main independent variables in the analysis are the skill level of the occupation and the types of tasks executed in the occupation. Information on which occupation workers had when entering non-standard employment in 2007 was available in 4-digit ISCO 2008. As a measure of the skill level of the occupation, an existing scale constructed by Statistics Netherlands was used, which is based on large-scale representative data that measures skill level as the mean number of years of education enjoyed by workers in that occupation (Menger & De Vries, 2017). So, for every individual in a given occupation, the occupational skill level is the same. However, within occupations, the individual level of education may vary. A squared term for the occupational skill level was included to allow for non-linearity. The types of tasks executed in occupations was operationalized using task scales created by Acemoglu and Autor (2011). They created scales to measure the importance of five tasks types in an occupation: non-routine analytic tasks, non-routine interactive tasks, routine cognitive tasks, routine manual tasks and non-routine manual tasks. These scales were based on information from the Occupational Information Network (O*NET) from 2007. The O*NET database contains 128 occupational characteristics, which all have scales that express the importance of that characteristic for that occupation on a scale of 1 to 7. The occupational codes in the O*NET database were matched to ISCO 2008, which allowed for the inclusion of these variables in the analysis as well. The task measures were created by taking the mean importance of several tasks that are relevant for the five task types of that occupation. Which exact tasks were included in the task measures, can be found in Appendix 4B or in Acemoglu & Autor (2011, p. 1163). Subsequently, these scales were standardized at the occupation level.[14]

The control variables include a categorical measure of working hours per week (<24 hours, 25-35 hours, 36+ hours) gender, age, age squared, level of education (low, medium and high education) and ethnicity (native Dutch, western migration background and non-western migration background). All control variables were measured at the moment that the individual entered the sample. Descriptive statistics on all independent variables per cluster group can be found in Appendix 4C.

4.4. Results

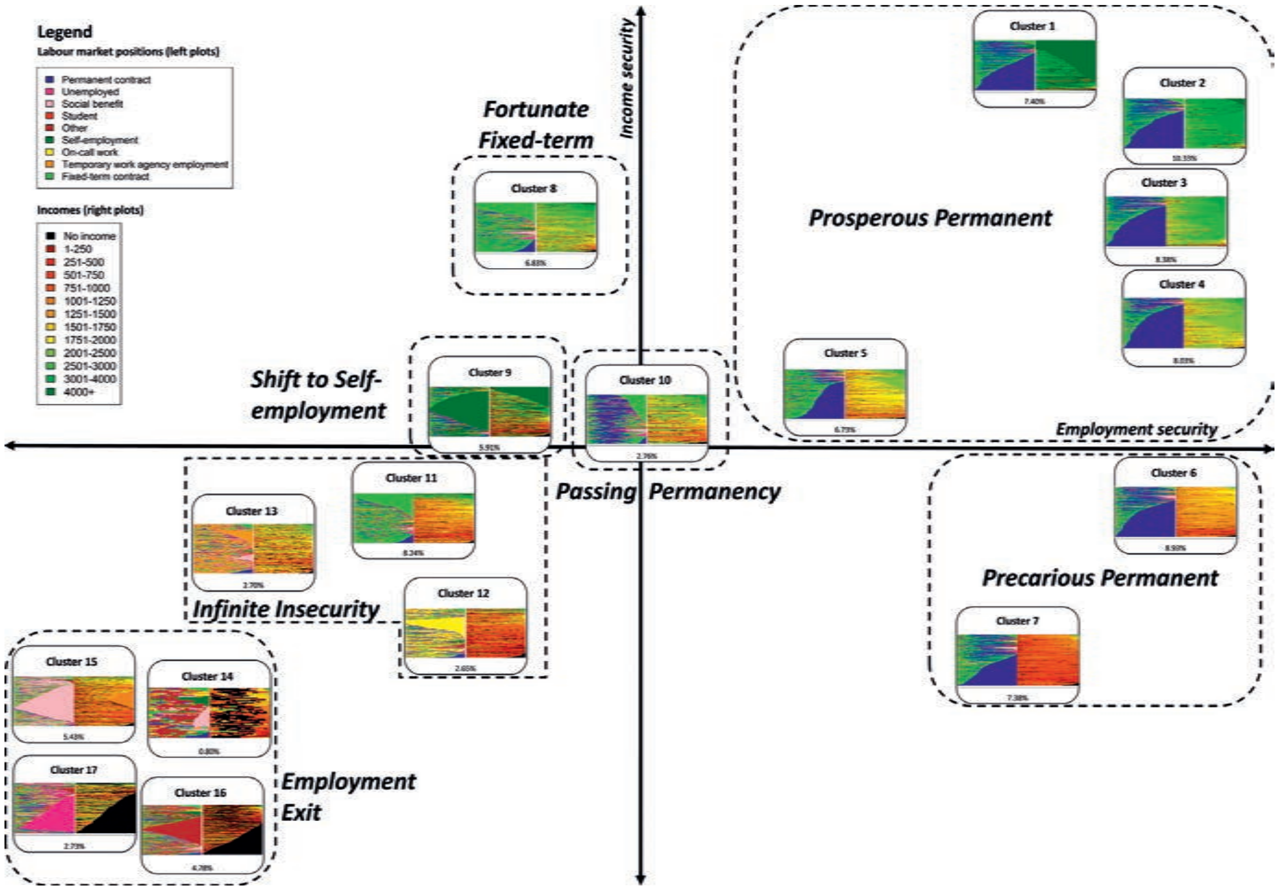
4.4.1. Typology of non-standard employment careers

Figure 4.1 presents the typology of non-standard employment careers that results from the multichannel sequence analysis. This typology consists of 17 career types that are classified based on employment and income security. The operationalisation of employment and income security can be found in Appendix 4A. The classification was subsequently used to group the clusters into larger cluster groups based on their similarity in employment and income security for the explanatory analysis. Each cluster group is given a name that broadly describes the types of trajectories that it includes. The small clusters plots in the figure are index plots (Scherer, 2001). These index plots consist of stacked horizontal lines. Every horizontal line represents an individual career that is present in that cluster, progressing over time from the left to the right. Colours depict the various labour market positions (left plots) and income levels (right plots) the individuals encounter during their career. For instance, many individuals start in fixed-term contracts (bright green in the left plots) and over time progress into permanent contracts (navy blue in the left plots).

The *stepping stone clusters* with both high levels of employment security and income security are located at the top right of the grid (clusters 1 to 5). In these clusters, workers make the transition to permanent employment relatively fast and earn decent and stable incomes during this process. For instance, workers in cluster 1 earn incomes of at least €4000 while making a quick transition to permanent employment. For workers in cluster 5, the transition to permanent employment takes somewhat longer, which results in lower employment security, while they earn incomes of around €1700. Together, these five clusters are combined in the cluster group *Prosperous Permanent* that contains 42% of the careers.

14 Data and codes prepared by the Institute for Structural Research, www.ibs.org.pl/resources

Figure 4.1: Dependent variable: a typology of non-standard employment careers



The *trap-clusters* in which workers both have low employment security and low income security, can be found at the opposite side of the grid, in the bottom-left quadrant. In clusters 14 to 17, non-employment plays a central role. For instance, workers in cluster 17 end up in unemployment, while workers in cluster 15 end up in welfare benefits. These clusters are combined in the cluster group *Employment Exit* that contains 12.2% of the careers. However, in this quadrant, there are also clusters consisting of careers where workers are employed in precarious types of non-standard employment and earn low and unstable incomes (clusters 11 to 13). These clusters are combined in the cluster group *Infinite Insecurity* that contains 13.6% of the careers.

The stepping stone and trap dichotomy does not describe all careers. The bottom right quadrant of the grid contains careers that have high employment security, but low levels of income security (clusters 6 and 7). These workers make the transition to permanent employment, but earn quite low wages, making them economically vulnerable. Wages are especially low in cluster 7, with workers earning on average only €800 monthly throughout their careers. These clusters clearly show that permanent employment is not necessarily a good outcome. These two clusters are combined in the cluster group *Precarious Permanent* and contain 15.7% of the careers.

Cluster 8, in the top left of the quadrant, consists of careers in which workers have low levels of employment security as they work mostly in fixed-term contracts, but earn quite high incomes, giving them high levels of income security. Therefore, this cluster can hardly be classified as precarious, as would be done in research focusing on transition to permanent employment. This cluster is called *Fortunate Fixed-term* and contains 8% of the careers.

Finally, two clusters are placed in the middle of the grid. In cluster 9, *Shift to Self-employment*, workers enter self-employment after some time. This is a very diverse group in terms of income security, as incomes vary from extremely low to extremely high. This makes this cluster harder to classify. This cluster contains 6% of the careers. In cluster 10, *Passing Permanency*, workers quickly make the transition to permanent employment, but return to fixed-term employment after some time. Some of these transitions are accompanied by income increases, others by income reductions. This cluster, containing 2.8% of the careers, shows that permanent employment is not necessarily the final outcome in careers, as workers either voluntarily or involuntarily leave their permanent positions.

The distribution of workers over the clusters deviates somewhat from the original typology of Mattijssen and Pavlopoulos (2019). The clusters in the top right quadrant are overrepresented (41% instead of 30%) while the clusters in the bottom left quadrant are underrepresented (27% instead of 40%). These differences probably appear due to the fact that the occupation was more often unknown for workers in more precarious careers, or due to the fact that workers with less fortunate social positions are in general less likely to participate in surveys (Te Riele, 2002) and therefore are also less likely to be included in these analyses based on linked survey-register data, while they were present in the register data used by Mattijssen and Pavlopoulos (2019).

4.4.2. The impact of occupations on the non-standard employment career

The effect of occupational skill level and task types on the type of trajectory followed by the workers is modelled with a multinomial logistic regression. The main results of this regression are presented in the form of the average marginal effects (Table 4.1). These average marginal effects show the absolute change in the probability of belonging to a certain career type resulting from a 1-unit increase of the independent variable. The average marginal effects for the control variables and the original regression coefficients from the multinomial logistic regression can be found in Appendix 4D.

Hypothesis 1 states that workers who enter non-standard employment in occupations with high-skilled tasks have more stable employment careers with fewer non-standard employment contracts and less unemployment (i.e. more employment security) as well as higher and more increasing incomes (i.e. more income security) than workers in occupations with low skilled tasks. Moreover, it was expected that this effect prevails even after controlling for the education level of the individual. These expectations are not fully confirmed. Higher-skilled occupations only significantly reduce the probability of having a *Precarious Permanent* career type. These careers have lower levels of income security, but still high levels of employment security. This effect is non-linear: the decline of the probability of having this career type fastens as the skill level increases. For the probability of having career types with lower levels of employment security and/or income security, the level of the tasks executed in the occupation is not relevant. The only exception is that workers in higher skilled occupations are more likely to make the *Shift to Self-employment*. Thus, high-skilled occupations do not protect against *Infinite Insecurity* or *Employment Exits*. It can however be said that, when employment security is achieved, workers in high-skilled occupations are less likely to experience low income security, as they are less likely to have a *Precarious Permanent* career.

Table 4.1: Marginal effects of the multinomial logistic regression with the cluster groups as dependent variable

	Prosperous Permanent	Precarious Permanent	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Infinite Insecurity	Employment Exit
Overall probability	0.415	0.158	0.080	0.028	0.060	0.122	0.137
	(0.006)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)
Occupational skill level	0.011	**-0.019*** **	0.001	0	**0.019*** **	-0.004	-0.008
	(0.006)	(0.005)	(0.004)	(0.002)	(0.004)	(0.005)	(0.005)
Occupational skill level²	0	**-0.002***	**0.002** **	-0.001	0	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0)	(0)	(0.001)	(0.001)
Task types							
Non-routine analytic	**0.036** **	**-0.026***	-0.007	0.002	**-0.013***	-0.001	0.009
	(0.012)	(0.011)	(0.007)	(0.005)	(0.006)	(0.01)	(0.01)
Non-routine interactive	**0.017***	0.012	0.003	0.003	-0.006	-0.013	**-0.016***
	(0.009)	(0.009)	(0.005)	(0.003)	(0.004)	(0.008)	(0.008)
Routine cognitive	**0.038*** **	-0.001	0.002	-0.001	**-0.026*** **	-0.002	-0.01
	(0.008)	(0.006)	(0.005)	(0.003)	(0.004)	(0.005)	(0.006)
Routine manual	**-0.038***	-0.018	0.006	**0.011***	0.013	0.006	**0.02***
	(0.013)	(0.011)	(0.008)	(0.005)	(0.007)	(0.009)	(0.01)
Non-routine manual	-0.011	-0.006	0	-0.004	**0.013***	0.012	-0.006
	(0.006)	(0.005)	(0.004)	(0.002)	(0.004)	(0.005)	(0.005)
Age	**0.001*** **	0.001	-0.001	-0.001	0.001	**-0.001*** **	**0.001*** **
	(0.001)	(0)	(0)	(0)	(0)	(0)	(0)
Age²	-0.0003	-0.00004	**-0.00007*** **	**0.00001***	**-0.00003** **	**0.00019** **	**0.00024***
	(0.00006)	(0.00004)	(0.00004)	(0.00002)	(0.00003)	(0.00004)	(0.00004)
Female	**-0.131*** **	**0.124*** **	-0.01	0.003	-0.013	0.018	0.009
	(0.015)	(0.011)	(0.009)	(0.006)	(0.008)	(0.012)	(0.012)
Level of education							
Low education	**-0.063*** **	**0.042*** **	-0.009	-0.006	-0.012	-0.002	**0.05*** **
	(0.016)	(0.011)	(0.009)	(0.005)	(0.008)	(0.011)	(0.011)
High education	**0.062*** **	-0.021	-0.012	0.007	0.003	**-0.041** **	0.003
	(0.017)	(0.013)	(0.01)	(0.007)	(0.009)	(0.012)	(0.013)
Education unknown	-0.021	0.006	0.002	-0.006	-0.015	-0.012	0.047
	(0.042)	(0.037)	(0.025)	(0.013)	(0.021)	(0.031)	(0.035)
Weekly working hours							
Small part-time	**-0.256*** **	**0.136*** **	**-0.063*** **	-0.006	0	**0.095*** **	**0.094*** **
	(0.016)	(0.012)	(0.009)	(0.006)	(0.009)	(0.013)	(0.014)
Large part-time	**-0.082*** **	**0.082*** **	**-0.04*** **	-0.002	-0.013	**0.028***	**0.026***
	(0.019)	(0.013)	(0.011)	(0.007)	(0.009)	(0.013)	(0.013)
Ethnicity							
Non-western background	**-0.101*** **	-0.026	**-0.033** **	-0.008	-0.015	0.029	**0.154*** **
	(0.02)	(0.014)	(0.01)	(0.006)	(0.01)	(0.015)	(0.018)
Western background	**-0.06** **	-0.008	-0.007	0.005	-0.01	0.023	**0.056** **
	(0.02)	(0.015)	(0.012)	(0.008)	(0.01)	(0.015)	(0.016)
AIC	17499,49						
BIC	18223.11						
N	6004						

* p<0.05, ** p<0.01, *** p<0.001

Furthermore, the results indicate, in contrast to hypothesis 1, that the individual level of education is more relevant for career development: the higher their level of education, the more likely individuals are to have a *Prosperous Permanent* career, with the difference between the highest and lowest level of education adding up to 12.5%-point. Those with lower levels of education are also more likely to have a *Precarious Permanent* career or to experience an *Employment Exit*, while the higher educated are less likely to experience *Infinite Insecurity*. Additional analyses (Appendix 4E), however, show that the effect of occupational skill level is partially confounded by the effect of individual skills. The limited effects of occupational skill level are thus likely due to the fact that individuals select themselves in occupations that match their individual skill level.

With respect to the type of tasks in the occupation, it was hypothesized that the careers of workers in routine occupations would be less stable in terms of employment, with more non-standard employment contracts and unemployment spells (i.e. lower levels of employment security), than the careers of workers in non-routine occupations, irrespective of income (H2a). Moreover, it was hypothesized that manual tasks lead to lower and more unstable incomes (i.e. lower levels of income security), irrespective of employment security (H2b). The results confirm the hypothesis on manual tasks (H2b) but provide contradicting evidence on routine tasks (H2a). The results show that routine manual tasks, such as operating machines, decrease the probability of having a *Prosperous Permanent* career – that entails high levels of employment and income security – while they increase the probability of experiencing an *Employment Exit*, which includes careers with both low employment and income security. Moreover, routine manual tasks increase the probability of experiencing *Passing Permanency*, which includes careers with a voluntary or involuntary termination of permanent employment. Taking these results together, routine manual tasks indeed result in lower levels of both employment security, due to being routine, and income security, due to being manual. This would mean, for instance, that conveyor belt workers are very likely to have precarious careers. Furthermore, both non-routine analytic tasks and non-routine interactive tasks increase the probability of having a *Prosperous Permanent* career, while non-routine analytic tasks protect against *Precarious Permanent* careers and non-routine interactive tasks protect against *Employment Exits*. Thus, these non-routine and non-manual tasks lead to the hypothesized higher levels of employment and income security. This would mean that non-standard employment leads to stepping stone careers for occupations such as teachers or researchers.

However, routine cognitive tasks have a different effect than routine manual tasks as they increase the probability of having a *Prosperous Permanent* career. Thus, workers in occupations such as accounting are more likely to have careers with high levels of both employment and income security. Non-routine manual tasks have no effect on the probability of belonging to any career type, except for an increased probability of making the *Shift to Self-employment*. These findings indicate that, contrary to the expectations, non-routine tasks do not guarantee high levels of employment security while routine tasks not necessarily result in low levels of employment security.

Taken together, these findings also point to another unexpected result: manual tasks are more important in predicting employment security than routine tasks. Non-routine analytic, non-routine interactive and routine cognitive tasks lead to career types with higher levels of employment security, while routine manual tasks lead to career types with lower levels of employment security. However, as non-routine manual tasks have no effects whatsoever, routine manual tasks mostly drive these findings.

4.5. Discussion

In the light of the increase of non-standard employment in the Netherlands, gaining insights in which workers are at risk of ending up in precarious careers due to these types of employment is crucial. Whereas research has originally focused on the effects of individual level characteristics on the career outcomes of non-standard employment, this chapter contributes to the existing literature by extending the scope to occupational characteristics as these are the factors that mostly determine employers' need and motives of the use of non-standard employment.

The results indicate that, although its effects remain limited, occupational skill level contributes to labour market inequalities. However, in contrast to what could be expected based on human capital theory and signalling theory, high skilled occupations do not protect against trap careers net of individual skill level. Moreover, the results indicate that employers seem to be more likely to base employment decisions on individual level skills rather than occupation level skills. Further research should pursue the latter topic as, in the data, only small numbers of low skilled individuals worked in high skilled occupations, and vice versa. However, the fact that some effects of occupational skill level remain, even after controlling for individual skill level, shows that this aspect is relevant in explaining inequalities in the outcomes of non-standard employment.

The results also show that occupational task types influence the career outcomes of non-standard employment, although the direction of the relationships is not always consistent with theory. Goldthorpe's (2007) framework suggests that workers are more replaceable in occupations with tasks that involve low skill specificity and low monitoring costs. So for these occupations, employers would mainly use non-standard employment contracts to achieve flexibility. Therefore it was expected that routine tasks, which combine low skill specificity and monitoring costs, would lead to unstable careers with repeated insecure contracts and unemployment (i.e. low employment security). However, contrary to this hypothesis, routine tasks as such do not determine career pathways. The combination of routine tasks and manual tasks, however, turns out to be crucial. In more detail, routine manual tasks lead to low employment security and income security. This is very interesting, as it implies that employers use short-term employment contracts combined with low salaries when the jobs they offer combine routine and manual tasks.

The importance of manual tasks in explaining employment security is surprising as it is not predicted by theory. There are two possible explanations for this. First, manual tasks are generally associated with lower skill levels, as it is often assumed that manual tasks are easier to learn than non-manual tasks (Mincer, 1958). However, as occupational skill level is controlled for, this explanation is not plausible. A second explanation could be that routine manual tasks result in better measurable output than routine cognitive tasks. This would implicate that the level of routine tasks alone is insufficient to fully capture Goldthorpe's (2007) dimensions of skill specificity and monitoring costs, and indicates that a combination of the importance of routine and manual tasks in an occupation could be a better measure.

Furthermore, the processual approach applied in this study has allowed investigating the effects of occupations on career quality in the dimensions of employment and income security, giving a more nuanced image of the existing labour market inequalities. With this approach, career outcomes that deviate from the traditional distinction between traps and stepping stones have been identified as well. However, these deviant career types, that combine high levels of employment security with low levels of income security, or vice versa, are not explained well by occupational characteristics. So, while occupations can clearly stratify between the stepping stone and trap careers, future research is necessary to identify which factors can explain these deviant career outcomes.

Though all opportunities offered by the data have been used to achieve these results, there are some limitations to this study. First, as the information on the workers' occupation is only available for 15 of the 96 months of the observation period, the impact of occupational changes on career outcomes cannot be assessed. Second, the main aspects of occupations that, according to theory, determine career outcomes – monitoring costs and skill specificity – are not directly observed in the data and are in general very difficult to measure. Though the combination of routine and manual tasks is believed to be a good indicator of monitoring costs and skill specificity, and the O*NET scales to be the best currently available measurement of tasks, direct measures of skill specificity and monitoring costs can improve the analysis. Moreover, the operationalization of occupational skill level could be improved, as the mean level of education of workers in that occupation, which again was the best indicator available, remains a relatively crude measure of occupational skill level. Future research using more detailed data should attempt to tackle these issues.

4.6. Conclusion

The aim of this study is to expand the literature on the determinants of the outcomes of non-standard employment by extending the focus to the extent to which occupational characteristics influence the career outcomes of non-standard employment, specifically focusing on the effects of the occupational skill level and occupational task types. By using a processual approach, multichannel sequence analysis, a typology of non-standard employment careers was created that classifies career types in terms of employment security and income security. Consequently, the results show that occupational skill level and occupational task types are relevant in explaining when workers experience the various career outcomes of non-standard employment. Most importantly, the results show that manual tasks are not only relevant in explaining differences between workers' careers in terms of income security, but are in combination with routine tasks also crucial in explaining differences in terms employment security. All in all, this chapter shows that occupations matter in determining career outcomes as they influence employers' hiring decisions. Policy makers can benefit from these results, as the results identify for which types of occupations non-standard employment functions as stepping stone, and for which occupations as a trap. Recent Dutch governments have already implemented several legislative changes in order to increase the number of transitions from non-standard to permanent employment. These policies, however, do not differentiate between different types of occupations. Making such a distinction is important for two reasons. First of all, especially workers in occupations in which non-standard employment functions as a trap have a need for policies aimed at increasing their employment security. Secondly, if employers have no need for long-term worker commitment, as seems to be the case in the routine manual occupations, legislation aimed at increasing the number of transitions from non-standard employment to permanent employment is less likely to be effective. In order to increase their employment security, these workers might be better off with policies that directly aim to improve their skills.

Appendices to chapter 4

Appendix 4A: Creation of the typology

The variable labour market position for the first channel of the sequence analysis is based upon two variables from the *System of social statistical datasets (SSD)* (Bakker et al., 2014): contract type and socio-economic position in a given month. The possible contract types are permanent contracts, fixed-term contracts, temporary work agency contracts, on-call workers and interns. The number of interns was, however, very small (<0.5%). Therefore, this group was merged with the fixed-term contracts. Furthermore, many studies on non-standard employment also include part-time employment in their analyses as a form of non-standard employment. Part-time employment is not included here as working hours are independent of contract type and part-time employment is usually voluntary in the Netherlands (Portegijs & Keuzenkamp, 2008).

For the individuals who were not in dependent employment, a distinction is made between the self-employed[15], the unemployed, those receiving non-work related welfare benefits, students, pensioners and a group in other states. Individuals are considered self-employed only when self-employment is their largest income source. Workers who combine self-employment and dependent employment cannot be observed. The number of workers receiving a pension benefit was limited (<0.5%). Therefore, this group is merged with the group of other states. The group 'other' is thus very heterogeneous, as it includes not only those receiving a pension benefit, but also inactive individuals and individuals with an unclassified labour force status. In total, there are 9 possible labour market positions (see Table 4A.1).

The second channel of the sequence analysis is based on monthly individual earnings from the main job or, in the absence of employment, from benefits. These are gross earnings, excluding special payments and bonuses. For the months in self-employment, the yearly earnings from self-employment are divided by the number of months someone was self-employed. The income of the self-employed is supplemented with income from other activities, such as freelancing. As sequence analysis treats all states nominally and computes costs for each state combination, it is impossible to include the worker's income as a continuous variable. Therefore, individual monthly income is classified into 13 categories (see Table 4A.1). For reference, the modal monthly income in the Netherlands varied from €2400 in 2007 to €2700 in 2015.

15 Workers who start their non-standard employment career in self-employment are not part of the population of this dataset, but when workers enter non-standard employment and consequently become self-employed, their later position as self-employed is registered.

Table 4A.1: Categories of sequence variables[16]

Labour market position	Gross monthly income (in €)
Permanent contract	No income
Unemployed	1-250
Social benefit	251-500
Student	501-750
Other	751-1000
Self-employment	1001-1250
On-call work	1251-1500
Temporary work agency employment	1501-1750
Fixed-term contract	1751-2000
	2001-2500
	2501-3000
	3001-4000
	4000+

The clustering of the career sequences was modelled to the typology of non-standard employment careers by Mattijssen and Pavlopoulos (2019).[17] For single channel sequence analysis, a procedure is included in TraMineR to model a typology on representative sequences. This procedure has not been developed yet for multichannel sequence analysis. Therefore, a detour was used to model the new typology to the representative sequences of the typology by Mattijssen and Pavlopoulos.

This process went as follows. First, medoid sequences from the 17 clusters of the typology created by Mattijssen and Pavlopoulos were extracted. These 17 medoid sequences were added to the dataset containing the sequences of the 6,004 observations. Consequently, a distance matrix was created using the same distance metric as Mattijssen and Pavlopoulos: an Optimal Matching procedure (Abbott & Forrest, 1986) with a *Hamming distance* cost setting with constant costs (Hamming, 1950) (more details about this distance metric can be found in Mattijssen and Pavlopoulos (2019)). This distance matrix thus contained the distances of the sample sequences to the medoid sequences of the clusters of the Mattijssen and Pavlopoulos typology. Finally, the sample sequences were placed in the cluster of the medoid sequence to which the distance was lowest. Some clusters could be placed in more than one cluster. They were randomly assigned to one of the clusters to which they had the lowest distance. This resulted in a typology

16 As the channels are constructed in the same way as done by Mattijssen and Pavlopoulos (2019), their previously printed table is used here as well.

17 Chapter 2 of this dissertation is a slightly altered version of Mattijssen and Pavlopoulos (2019).

consisting of 17 clusters that are substantially similar to the original Mattijssen and Pavlopoulos typology.

The clusters are placed on a grid with employment security on the horizontal axis and income security on the vertical axis. The employment and income security of the clusters are determined qualitatively, as a combination of quantitative measures did not lead to a classification that fully rendered justice to the qualitative conception of the clusters' employment and income quality. Other research has also aimed at creating employment precarity indices (Ritschard, Bussi, & O'Reilly, 2018), but the results have not been satisfactory. Therefore, the clusters have been placed qualitatively, taking into account the time spent in employment, the mean duration until the transition to permanent employment is made, the number of job changes and the types of employment encountered in the cluster. Income security is determined looking at the mean within-career income and the within-career standard deviation of the income. It is stressed that the grid is a graphic help for the interpretation of results and that distances between clusters are not based on calculations.

Such a large amount of clusters does justice to the complexity of the labour market, but complicates explanatory analyses. Therefore, the clusters were regrouped into larger cluster groups based on similarity in employment and income security. This resulted in seven cluster groups, which are given names that broadly describe the careers that are present in the cluster group. Cluster group *Prosperous Permanent* consists of clusters 1 to 5, cluster group *Precarious Permanent* consists of clusters 6 and 7, cluster group *Infinite Insecurity* consists of clusters 11 to 13 and cluster group *Employment Exit* consists of clusters 14 to 17. Cluster 8, 9 and 10 form cluster groups on their own, as there are no clusters similar to them in terms of employment and income security. Cluster 8 is called *Fortunate Fixed-term*, cluster 9 is called *Shift to Self-employment* and cluster 10 is named *Passing Permanency*.

Appendix 4B: Task scales

The task measures were created following the approach by Acemoglu and Autor (2011), using syntax created by the Institute for Structural Research.[18]

The scale for non-routine analytical tasks consists of the importance of:

- Analysing data/information
- Thinking creatively
- Interpreting information for others

The scale for non-routine interactive tasks consists of the importance of:

- Establishing and maintaining personal relationships
- Guiding, directing and motivating subordinates
- Coaching/developing others

The scale for routine cognitive tasks consists of the importance of:

- Repeating the same tasks
- Being exact or accurate
- Structured versus unstructured work (reverse coded)

The scale for routine manual tasks consists of the importance of:

- Pace determined by speed of equipment
- Controlling machines and processes
- Spending time making repetitive motions

The scale for non-routine manual tasks consists of the importance of:

- Operating vehicles, mechanized devices, or equipment
- Spending time using hands to handle, control or feel objects, tools or controls
- Manual dexterity
- Spatial orientation

For each scale, the mean score of the included items was calculated. Consequently, these scores were standardized on the occupational level.

18 www.ibs.org.pl/resources

Appendix 4C: Descriptive statistics

Table 4C.1: Descriptive statistics of categorical variables (%)

	Gender		Weekly working hours			Level of education				Ethnicity			N
	Male	Female	Small part-time	Large part-time	Full-time	Low education	Middle education	High education	Education unknown	Native Dutch	Non-western background	Western background	Abs. N in ( )
Precarious Permanent	12.58	87.42	64.06	19.34	16.6	36.89	47.78	14.06	1.27	81.29	9.73	8.99	15.76 (946)
Prosperous Permanent	58.97	41.03	14.48	16.29	69.23	16	42.84	39.31	1.85	85.4	6.46	8.14	41.52 (2493)
Fortunate Fixed-term	58.39	41.61	14.7	13.25	72.05	22.77	48.03	26.71	2.48	84.89	6.42	8.7	8.04 (483)
Infinite Insecurity	34.88	65.12	49.05	15.94	35.01	32.83	51.09	14.17	1.91	76.7	12.81	10.49	12.23 (734)
Employment Exit	37.18	62.82	47.51	15.8	36.7	40.1	40.34	17.13	2.43	67.19	21.02	11.79	13.71 (823)
Passing Permanency	47.9	52.1	23.95	16.77	59.28	19.76	47.9	30.54	1.8	82.63	6.59	10.78	2.78 (167)
Shift to Self-employment	50.84	49.16	29.05	14.25	56.7	17.32	42.74	38.55	1.4	85.2	6.7	8.1	5.96 (358)
Total	44.89	55.11	32.2	16.31	51.5	25.38	44.84	27.91	1.87	81.06	9.76	9.18	(6004)

Table 4C.2: Descriptive statistics of continuous variables

	Non-routine analytic		Non-routine interactive		Routine cognitive		Routine manual		Non-routine manual		Occupational skill level		Age	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Precarious Permanent	-0.776	0.892	-0.310	0.800	0.092	0.962	-0.216	0.701	-0.264	0.667	12.487	1.682	37.235	9.824
Prosperous Permanent	0.140	0.923	0.211	0.905	0.171	0.889	-0.342	0.812	-0.372	0.971	13.992	2.282	35.572	9.402
Fortunate Fixed-term	-0.118	0.905	0.055	0.918	0.184	0.809	-0.107	0.871	-0.109	1.002	13.302	2.359	33.776	9.319
Infinite Insecurity	-0.592	0.908	-0.254	0.840	0.141	0.931	-0.044	0.777	-0.043	0.866	12.527	1.892	35.448	10.930
Employment Exit	-0.613	0.992	-0.254	0.864	0.087	0.938	0.002	0.795	-0.035	0.864	12.464	1.989	37.510	11.090
Passing Permanency	-0.131	0.919	0.087	0.904	0.209	0.872	-0.111	0.828	-0.173	0.919	13.303	2.056	34.042	9.825
Shift to Self-employment	0.055	1.000	0.172	0.951	-0.176	0.898	-0.316	0.771	-0.264	0.924	14.090	2.484	37.316	9.674
Total	-0.230	1.005	-0.010	0.909	0.125	0.910	-0.211	0.803	-0.236	0.911	13.298	2.242	36.002	9.990

Appendix 4D: Full results

Table 4D.1: Results of multinomial logistic regression with clusters groups as dependent variable

	Precarious Permanent	Fortunate Fixed-term	Infinite Insecurity	Employment Exit	Passing Permanency	Shift to Self-employment
	b/se	b/se	b/se	b/se	b/se	b/se
Occupational skill level	**-0.220*** **	-0.023	-0.109*	**-0.141** **	-0.058	**0.288*** **
	(0.053)	(0.053)	(0.050)	(0.048)	(0.090)	(0.067)
Occupational skill level²	-0.018	**0.020***	0.004	0.003	-0.023	-0.009
	(0.010)	(0.008)	(0.009)	(0.008)	(0.017)	(0.009)
Task types						
Non-routine analytic	**-0.324** **	-0.182	-0.144	-0.065	-0.014	**-0.315** **
	(0.108)	(0.106)	(0.103)	(0.100)	(0.177)	(0.120)
Non-routine interactive	0.013	-0.003	**-0.169***	**-0.185***	0.043	-0.159
	(0.084)	(0.074)	(0.078)	(0.074)	(0.121)	(0.084)
Routine cognitive	**-0.134***	-0.077	**-0.136***	**-0.198*** **	-0.145	**-0.547*** **
	(0.061)	(0.068)	(0.061)	(0.059)	(0.111)	(0.078)
Routine manual	-0.008	0.175	0.163	**0.260***	**0.483** **	**0.323***
	(0.109)	(0.116)	(0.104)	(0.101)	(0.181)	(0.140)
Non-routine manual	-0.011	0.033	0.122	-0.013	-0.102	**0.258***
	(0.103)	(0.102)	(0.098)	(0.095)	(0.168)	(0.117)
Age	0.002	**-0.019*** **	**-0.012** **	0.006	**-0.020***	**0.014***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.008)	(0.006)
Age²	**0.001** **	-0.000	**0.003*** **	**0.003*** **	0.001	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Female	**1.563*** **	0.234	**0.676*** **	**0.608*** **	**0.497***	0.162
	(0.136)	(0.126)	(0.121)	(0.117)	(0.204)	(0.148)
Ethnicity (ref: Native Dutch)						
Non-western background	**0.349***	-0.183	**0.696*** **	**1.332*** **	-0.009	0.042
	(0.159)	(0.207)	(0.152)	(0.135)	(0.329)	(0.233)
Western background	0.231	0.089	**0.436** **	**0.652*** **	0.356	0.006
	(0.156)	(0.180)	(0.154)	(0.145)	(0.264)	(0.211)
Level of education (ref: medium education)						
Low education	**0.594*** **	0.074	**0.281***	**0.646*** **	-0.023	-0.009
	(0.111)	(0.138)	(0.114)	(0.111)	(0.227)	(0.171)
High education	**-0.413** **	**-0.301***	**-0.601*** **	-0.209	0.034	-0.126
	(0.136)	(0.144)	(0.144)	(0.136)	(0.219)	(0.159)
Education unknown	0.160	0.081	0.008	0.436	-0.160	-0.219
	(0.361)	(0.337)	(0.331)	(0.301)	(0.613)	(0.487)
Weekly working hours (ref: full-time)						
Small part-time	**2.024*** **	-0.079	**1.693*** **	**1.642*** **	**0.575***	**0.742*** **
	(0.128)	(0.163)	(0.125)	(0.122)	(0.230)	(0.164)
Large part-time	**1.017*** **	-0.245	**0.558*** **	**0.524*** **	0.151	-0.029
	(0.139)	(0.158)	(0.140)	(0.136)	(0.238)	(0.181)
Constant	**-3.224*** **	**-1.661*** **	**-2.495*** **	**-2.650*** **	**-3.016*** **	**-2.057*** **
	(0.143)	(0.111)	(0.119)	(0.118)	(0.193)	(0.127)
AIC	17499.490					
BIC	18223.109					
N	6004					

* p<0.05, ** p<0.01, *** p<0.001
Dependent variable reference category: Prosperous Permanent

Appendix 4E: Additional analysis

In this analysis, individual level of education was excluded from the analysis, to see whether the effect of occupational skill level would have been stronger without controlling for level of education. This turns out to have been the case (Table 4D.2).

Table 4D.2: Marginal effects of the multinomial logistic regression with the cluster groups as dependent variable, without level of education

	Prosperous Permanent	Precarious Permanent	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Infinite Insecurity	Employment Exit
Overall probability	0.415	0.158	0.080	0.028	0.060	0.122	0.137
	(0.006)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)
Occupational skill level	**0.021****	**-0.024*****	0.001	0.001	**0.020*****	-0.007	**-0.011***
	(0.006)	(0.005)	(0.003)	(0.002)	(0.004)	(0.004)	(0.005)
Occupational skill level²	0	**-0.002***	**0.002****	-0.001	-0.001	0	0.001
	(0.001)	(0.001)	(0.001)	(0)	(0)	(0.001)	(0.001)
Task types							
Non-routine analytic	**0.039****	**-0.027***	-0.007	0.003	-0.012	-0.002	0.007
	(0.012)	(0.011)	(0.007)	(0.005)	(0.006)	(0.01)	(0.01)
Non-routine interactive	**0.018***	0.011	0.003	0.003	-0.006	-0.013	**-0.016***
	(0.009)	(0.009)	(0.005)	(0.003)	(0.004)	(0.008)	(0.008)
Routine cognitive	**0.038*****	-0.001	0.002	-0.001	**-0.026*****	-0.001	-0.011
	(0.008)	(0.006)	(0.005)	(0.003)	(0.004)	(0.005)	(0.006)
Routine manual	**-0.041****	-0.015	0.006	**0.01***	0.012	0.006	**0.022***
	(0.013)	(0.011)	(0.008)	(0.005)	(0.007)	(0.009)	(0.01)
Non-routine manual	-0.014	-0.005	0.001	-0.004	**0.014***	0.013	-0.005
	(0.012)	(0.011)	(0.007)	(0.004)	(0.006)	(0.009)	(0.01)
Age	0.001	0.001	**-0.001****	-0.001	**0.001****	**-0.001****	**0.001***
	(0.001)	(0)	(0)	(0)	(0)	(0)	(0)
Age²	**-0.00032****	-0.00003	-0.00007	0.00001	-0.00003	**0.00019*****	**0.00025*****
	(0.00006)	(0.00004)	(0.00004)	(0.00002)	(0.00003)	(0.00004)	(0.00004)
Female	**-0.131*****	**0.124*****	-0.01	0.003	-0.013	0.018	0.009
	(0.016)	(0.011)	(0.009)	(0.006)	(0.008)	(0.012)	(0.012)
Weekly hours worked							
Small part-time	**-0.260*****	**0.138*****	**-0.063*****	-0.007	0	**0.097*****	**0.094*****
	(0.017)	(0.012)	(0.009)	(0.006)	(0.009)	(0.013)	(0.014)
Large part-time	**-0.086*****	**0.085*****	**-0.04*****	-0.002	-0.013	**0.029***	**0.028***
	(0.019)	(0.013)	(0.011)	(0.007)	(0.009)	(0.013)	(0.013)
Ethnicity							
Non-western background	**-0.105*****	-0.024	**-0.033****	-0.009	-0.016	0.028	**0.159*****
	(0.019)	(0.014)	(0.01)	(0.006)	(0.01)	(0.015)	(0.019)
Western background	**-0.062****	-0.008	-0.006	0.005	-0.01	0.024	**0.058*****
	(0.02)	(0.015)	(0.012)	(0.008)	(0.01)	(0.015)	(0.016)
AIC	17550.23						
BIC	18153.25						
N	6004						

5

Scarred by your employer?

The effect of employers' strategies on the career outcomes of non-standard employment

Abstract

A central mechanism in explaining the outcomes of non-standard employment for workers is the strategy employers use for non-standard employment: screening, workforce adaptability or cost reduction. In this chapter, we investigate the role of this mechanism by studying the effect of employer strategies on the employment and income trajectories of workers in the Netherlands who started employment with a non-standard contract in 2010. To investigate the outcomes of non-standard employment, we classify employment and income trajectories in a typology using multichannel sequence analysis. The results show that workers starting employment in firms that predominantly use non-standard employment as a screening device are more likely to have subsequent careers with high levels of employment security than workers in firms with adaptability strategies. However, strong scarring effects are only found for workers who start employment in firms with cost reduction strategies: they are most likely to experience precarious careers characterized by non-employment.

This chapter is based on: Mattijssen, L., Pavlopoulos, D. & Smits, W. (2021). Scarred by your employer? The effect of employers' strategies on the career outcomes of non-standard employment. Unpublished manuscript.

5.1. Introduction

Non-standard employment – i.e. fixed-term employment, on-call employment, temporary work agency employment or self-employment – has become a structural part of European labour markets. Many countries have experienced a significant growth of various forms of non-standard employment, with many workers experiencing some kind of non-standard employment at some time during their career. The growth of non-standard employment has also resulted in a large body of research on this topic. Researchers have, amongst other things, investigated which institutional factors facilitated the growth of non-standard employment (Hevenstone, 2010; Hipp, Bernhardt, & Allmendinger, 2015; Muffels & Luijkx, 2008), whether firms' productivity is harmed by non-standard employment (Castellani, Lotti, & Obando, 2020; Lisi & Malo, 2017), but first and foremost research has focused on one central question: to what extent does non-standard employment function as a stepping stone to more stable, permanent employment, or as a trap resulting in spells of non-standard employment and unemployment (e.g. Booth et al., 2002; Gash, 2008; Giesecke & Groß, 2003; Hopp et al., 2016; Mooi-Reci & Dekker, 2015; Pavlopoulos, 2013; Scherer, 2004)?

In answering this pivotal question, research has mostly overlooked a crucial factor in determining whether non-standard employment leads to a stepping stone or a trap: employers' strategies for using non-standard employment (Bills, Di Stasio, & Gërxhani, 2017). Research has focussed solely on the role of macro-level factors, such as employment protection, unemployment benefits and industrial relations (Babos, 2014; Berton et al., 2011; Cahuc, Charlot, & Malherbet, 2016; Scherer, 2004), or into individual factors, such as gender, age and education (Booth et al., 2002; Giesecke & Groß, 2003). Although these micro-level and macro-level characteristics affect the hiring decisions of the employer, the strategies that employers – consciously or unconsciously – follow with respect to the use of non-standard employment contracts are crucial in determining the careers of workers with non-standard employment contracts. In some firms, non-standard contracts are typically used to screen the productivity of new hires. In these firms, workers with non-standard contracts will get training and gain human capital, non-standard contracts will be converted to permanent ones faster and wages will rise more quickly. In other firms, non-standard employment is mostly used to adapt to temporary demand fluctuations, while in a third group of firms non-standard employment is more often used as a means to reduce labour costs (De Beer, 2018). Starting a non-standard job in a firm belonging to any of these two latter groups may have long-term scarring effects in the career of the individual worker.

In the broad field of research on the outcomes of non-standard employment, there has been hardly any focus on studying the effect of employers' strategies on the career of individual workers. Some pertinent studies relate firm characteristics, such as output volatility or unionization, to the ways in which firms use non-standard employment (Ghosh, Willinger, & Ghosh, 2009; Masui, 2020; Portugal & Varejão, 2009). Others investigate the effect of the use of non-standard employment on firm productivity, and in that way try to derive employers' strategies (Castellani et al., 2020; Lisi & Malo, 2017). Again others have tried to link stated employer strategies to firms' use of non-standard employment (Hakim, 1990; Lasierra, 2007). Up to this point, however, there has been no research that explicitly links employers' non-standard employment strategies to the employment outcomes of the non-standard workers in that firm.

This chapter aims to fill this gap in the literature by investigating how the non-standard employment strategy of the firm affects the careers of workers who start working in this firm with a non-standard employment contract. We do so by investigating the careers of workers who start working in non-standard employment in the Netherlands in 2010, with a multidimensional, processual approach. With this approach, we can determine the quality of the outcomes of non-standard employment on all events that occur in the career in terms of employment positions and incomes. This way, we can move beyond the often used classification of outcomes based on transition rates from non-standard to permanent employment, and classify careers based on the employment and income security they offer workers.

The rest of this chapter is structured as follows. First, we discuss the three strategies employers can have for using non-standard employment, how these strategies are related to the outcomes of non-standard employment, and how these strategies can be detected. We also briefly discuss the rationale behind our multidimensional processual approach. Second, we discuss the data and methodology of the processual approach used in the analyses. We describe how we measured employers' strategies and our analytical strategy. Third, we discuss the outcomes of the processual approach – a typology of non-standard employment trajectories – and how employer strategies are linked to these outcomes. We also present results of dominance analyses that show which factors matter most in explaining outcomes of non-standard employment. Fourth and finally, we draw conclusions based on our results and make suggestions for future research.

5.2. Theoretical framework

5.2.1. Defining non-standard employment

Non-standard employment is usually employment with a permanent contract with fixed working hours. This means that the concept of non-standard captures a very broad range of employment types that all offer employers some type of flexibility. In this chapter, we investigate the outcomes of types of non-standard employment that offer employers numerical flexibility: opportunities to adapt the number of workers in the firm (Atkinson, 1984). Specifically, we focus on fixed-term employment and on-call employment. The first type is a form of external numerical flexibility and allows employers to adapt their workforce by turning to the external labour market. The last type is a form of internal numerical flexibility and allows employers adapt their workforce without turning to the external labour market (De Beer et al., 2011). Temporary work agency employment and self-employment are considered to be types of employment that offer external numerical flexibility as well, but due to data limitations, we cannot investigate the outcomes of workers who start working in temporary work agency employment or as self-employed. Part-time employment is considered to be a form of internal numerical flexibility, but in the context of this study – the Netherlands – part-time employment is so common that it is generally not considered to be a type of non-standard employment (Portegijs & Keuzenkamp, 2008). Therefore, we do not include part-time employment in our definition of non-standard employment and in our analyses.

5.2.2. Firms' strategies for using non-standard employment

There are three main strategies that employers may have for using non-standard employment in their organization. All three strategies have in common that they make use of one main characteristic of non-standard employment, namely that non-standard employment offers employers a relatively cheap method to discharge workers due to the lower firing costs compared to permanent contracts (Portugal & Varejão, 2009).

The first strategy is related to the original purpose of most forms of non-standard employment: to offer firms possibilities for *adapting their workforce to economic fluctuations* (Atkinson, 1984). Non-standard employment allows employers to adapt the workforce quickly, for instance by hiring new workers when demand increases and laying them off without high firing costs when demand decreases again. Non-standard employment is thus used to create a flexible periphery around the core staff. Fixed-term contracts or temporary work agency contracts are for instance very suitable for these kinds of circumstances, as well as on-call work, that allows employers to also adapt the number of working hours to the demand fluctuations. Non-standard employment can also be used to hire replacements when core employees are temporarily unavailable, for instance due to illness or leave (Portugal & Varejão, 2009). When firms require specialist knowledge that is not available within the firm, they can also make use of non-standard employment. In such situations, however, firms generally use independent contractors, a group that generally prefers working outside of a formal employment relationship (Abraham & Taylor, 1996; Kalleberg, 2000; Lautenbach et al., 2017).

The second strategy for using non-standard employment is *cost reduction*. This strategy is found amongst employers who do not limit the use of non-standard employment to a flexible periphery, but take the opportunity to benefit from the advantages of non-standard employment throughout the firm, also for jobs that are not susceptible to economic fluctuations. If there is no necessity for employers to create a long-term relationship with their workers, using non-standard employment rather than permanent employment can be an easy way to reduce costs. This is for instance the case for employers who offer work that does not require firm-specific skills and can easily be monitored (Abraham & Taylor, 1996). As many people could do that kind of work, workers are easily replaceable, making a long-term employment relationship superfluous. The main difference with employers who mainly use non-standard employment to deal with economic fluctuations and replacement, is thus that cost-reducing employers are also likely to use non-standard employment instead for jobs that are not susceptible to economic fluctuations if that is more profitable.

A third strategy for employers to use non-standard employment is *screening*. Although the labour law offers employers the possibility to use a probation period for new hires, in some cases this period is rather short to reveal the productivity of workers. Non-standard contracts offer a convenient, low-risk method for employers to extend the probation period of new hires (Spence, 1973). If the worker meets the employer's productivity and quality requirements, the employer is likely to offer the employee a permanent contract. If the worker does not meet the requirements, the employer can simply not extend the non-standard contract and lay-off the worker without high firing costs (Portugal & Varejão, 2009).

5.2.3. Outcomes of non-standard employment

The employers' strategies that are discussed above are related to the core mechanisms that explain the outcomes of non-standard employment for workers. There are two main scenarios that predict the outcomes of non-standard employment. The first scenario, the *stepping stone scenario*, argues that employers mostly use non-standard employment for screening workers (Booth et al., 2002). As in many cases screening will be successful, non-standard employment will for workers mostly function as a stepping stone to permanent employment at that firm. However, these types of non-standard employment may also benefit workers when moving to other firms. If employers use non-standard employment to screen workers, they will likely already invest in training workers during their non-standard contract period. This additional human capital might also be an advantage for these workers when they leave the firm (voluntarily or involuntarily) and are looking for employment elsewhere (Booth et al., 2002).

The second, opposing scenario, the *trap scenario*, argues that employers mostly use non-standard employment to adapt their workforce to economic fluctuations or to reduce labour costs (Giesecke & Groß, 2003; Houseman, 2001). As it is not part of this strategy to offer permanent contracts to their non-standard workers, in this scenario non-standard employment would not result in stable employment at the same firm. Furthermore, when these workers re-enter the labour market, their non-converted non-standard job might also have a scarring effect on their subsequent labour market chances: employers are less likely to invest in the human capital of non-standard workers who they do not intend to give a permanent contract. This is likely to result in a human capital disadvantage or human capital depreciation that will also harm the future employment prospects of this group of workers (Booth et al., 2002). Next to this, potential new employers might attribute the non-conversion of the previous non-standard job to the individual, and interpret it as a signal of lower quality. These employers might decide not to hire these workers, or to give them a non-standard contract to begin with. For workers, this process results in repeated spells of non-standard employment and unemployment, making non-standard employment a trap for them (Mooi-Reci & Dekker, 2015).

Following these scenarios, workers in firms with screening strategies would have better employment outcomes, while workers in firms with adaptability or cost reduction strategies would have worse employment outcomes. However, it is likely that working in firms with cost reduction strategies has an even stronger scarring effect on the further career development than working in firms with adaptability strategies. Though in both types of firms it is likely that employers do not invest much in the human capital of their workers with non-standard contracts, workers from firms with adaptability strategies might still be able to explain to future employers that the reason they were not able to continue at their previous job was that their work had a temporary nature, due to replacement or economic fluctuations. This way, they can show that the reason they left their previous employer is not due to their lower productivity or quality. However, as firms with cost reduction strategies use non-standard employment also for jobs that are not susceptible to economic fluctuations, workers from such firms cannot use this explanation. Next to this, making a strong case that their previous employers have cost reduction strategies and no intention to offer permanent contracts is much more difficult.

Therefore, for this group of workers, the non-conversion of their previous non-standard contract might more often be seen as a signal of lower quality by future employers, resulting in a stronger scarring effect.

5.2.4. Detecting employers' non-standard employment strategies

Employer strategies for using non-standard employment are thus a crucial mechanism in explaining the outcomes of non-standard employment. However, determining employer strategies for using non-standard employment is not straightforward. The biggest difficulty in this is that it is questionable whether all employers have an explicit, consciously determined strategy for their use of non-standard employment. Several studies show that many employers use ad hoc non-standard employment in response to external factors beyond their control (Peel & Boxall, 2005; Stanworth & Druker, 2006). The way non-standard employment is used is then not part of a conscious strategy with a clear motive. Another share of employers use non-standard employment mostly because they are mimicking the actions of their competitors (De Beer, 2018).

Next to this, when employers do say that they have an explicit strategy for using non-standard employment, there exists a large mismatch between what employers say they do, and what employers actually do in practice. Hakim (1990) for instance finds that firms that say they have different reasons for using non-standard employment actually do not differ that much in their use of non-standard employment. Lasierra (2007) also finds that stated strategies are not strongly linked to various uses of non-standard employment. So, using information based on what employers say they do might not be very reliable to use to predict the outcomes of non-standard employment.

Given the absence or ambiguity of strategies as thought-trough plans, we concur with Mintzberg (1978) and Procter et al. (1994) that strategies could also be defined as "a pattern in a stream of decisions" (Mintzberg, 1978, p. 935). Though employers do not have a conscious strategy for their use of non-standard employment, or do not practice what they preach, the way these employers use non-standard employment formulates such a consistent pattern that it has consequences for workers. In this chapter, we infer employers' strategies for using non-standard employment not from what they say that they do, but from what they actually do concerning non-standard employment. In other words, we use the established practices on the use of non-standard employment to derive the underlying – conscious or unconscious – strategies of employers for using non-standard employment. We have identified several practices that could be relevant indicators of strategies: the share of various types of non-standard employment, the transition rate from fixed-term to permanent employment and excess mobility.

The shares of various types of non-standard employment can reveal the strategies employers may have when using non-standard employment (Ono & Sullivan, 2013). Employers with screening strategies will mostly use non-standard employment for new hires. For this purpose, fixed-term contracts are better suited than temporary work agency employment and on-call contracts. As a result, employers with screening strategies are likely to have low shares of fixed-term employment and practically no temporary work agency workers or on-call workers. Employers with adaptability strategies are expected to have low to moderate levels of fixed-term employment, as they limit the use of non-standard employment to jobs that are susceptible to economic fluctuations. As temporary work agency employment and on-call work are well suited for offering adaptability (Houseman, 2001), employers with adaptability strategies are also expected to have relatively high levels of temporary work agency employment and on-call employment compared to employers with other strategies. Employers with cost reduction strategies are likely to aim to have as many fixed-term contracts as profitable. As a result, it is likely that these employers with have high levels of fixed-term employment. However, this is not necessarily reflected in a high share of temporary work agency workers or on-call workers. Hiring workers via a temporary work agency is also associated with additional costs. At the same time, hiring via a temporary work agency also offers opportunities to circumvent collective labour agreements, as temporary work agency workers fall under their own collective labour agreement and not the one that applies to the firm. Whether it is beneficial to hire workers on a temporary work agency contract is thus likely to depend on the sector and the collective agreement. This makes it difficult to link cost reduction strategies to a fixed share of temporary work agency employment. On-call work could also provide an option to reduce costs in the margins, for instance because workers can be sent home when work is finished earlier than expected. However, the use of on-call work is not as strong a cost-reducing mechanism as the use of fixed-term contracts is.

A second practice that gives insights in which strategies employers may have for their use of non-standard employment is the transition rate from fixed-term to permanent employment (Masui, 2020). In firms that use non-standard employment to screen workers, relatively many fixed-term workers will make the transition to permanent employment, as application procedures are usually quite capable of selecting good workers. Employers who use non-standard employment to achieve workforce adaptability or to reduce costs will have only a low share of fixed-term workers transitioning to permanent employment, as demand fluctuations do not allow it, the replacement period is over, or because it is an unnecessary expense for the employer.

The third practice is related to the previous one: excess mobility. Excess mobility is all influx and outflow of workers that is not required to achieve the net growth or shrinkage of the firm. Firms that use non-standard employment as a way to achieve adaptability will have a relatively large amount of excess mobility, as many new hires will be laid off as soon as demand decreases again. The same holds for employers who use non-standard employment to reduce costs, who constantly replace workers on non-standard contracts by new workers on non-standard contracts. This means a large influx and outflow of workers, without this being related to the growth or shrinkage of the firm. On the other side, firms that use non-standard employment as a screening method will have relatively low excess mobility, as a large share of the new hires will stay at the firm.

An overview of these non-standard employment practices can be found in Table 5.1. This table shows what scores the ideal types of the three strategies for using non-standard employment would have on the practices. Firms that have screening strategies are ideally characterized by low shares of fixed-term contracts, practically no temporary work agency and on-call employment, a relatively high transition rate from fixed-term to permanent employment and low levels of excess mobility. Firms that have workforce adaptability strategies for using non-standard employment ideally have low to medium levels of fixed-term employment, relatively high shares of temporary work agency and on-call employment, low transition rates from fixed-term to permanent employment and medium levels of excess mobility. Finally, firms that have cost-reduction strategies for using non-standard employment ideally have high levels of fixed-term employment, no fixed levels of temporary work agency and on-call employment, low transition rates from fixed-term to permanent employment and high levels of excess mobility.

Table 5.1: Non-standard employment practices per employer strategy

	Associated non-standard employment practices					Outcomes
Strategy	Share of fixed-term contracts	Share of temporary work agency contracts[1]	Share of on-call contracts	Transition rate	Excess mobility	Outcomes for workers with non-standard contracts
Screening	Low	Low	Low	High	Low	High employment and income security
Workforce adaptability	Low to medium	High	High	Low	Medium	Medium employment and income security
Cost reduction	High	Mixed	Mixed	Low	High	Low employment and income security

[1] Theoretical indicator only, this indicator could not be included in the analyses due to a lack of information.

Theoretically, these are all important indicators of employers' non-standard employment strategies. Ideally, we would include all these indicators in our analyses. However, we cannot include the share of temporary work agency workers in our analyses. In register data, workers with temporary work agency contracts are not registered in the firm where they actually work, but in the temporary work agency itself. As a result, we cannot derive from register data how many temporary work agency workers firms have hired, and thus cannot not include this practice in our analyses.

Though we have linked each strategy to non-standard employment practices, this does not mean that there are hard cut-off points on these practices that strictly distinguish the three strategies from each other.[19] Table 1 shows example scores for ideal types of the strategies and allow us to relate the strategies to the non-standard employment practices. In practice, most firms will not fit perfectly into any of the three main strategies: HR strategies might be more variable in practice, and firms might have various strategies for different types of jobs within the firm. Unfortunately, it is not possible to distinguish strategies on the job-level.

We will test the following expectations. First, we expect that workers who start in non-standard employment in firms with screening strategies have the best employment outcomes in terms of employment and income security. Second, workers who start their career in firms with workforce adaptability strategies are expected to be less likely to experience careers characterized by high levels of employment and income security, but not necessarily more likely to experience precarious careers characterized by non-employment as the scarring effect might remain limited. So, we expect these workers to have medium levels of both employment and income security. Third and finally, workers in firms with cost reduction strategies are most likely to have careers characterized by unstable non-standard employment or non-employment as they are likely to experience a stronger scarring effect of non-standard employment.

5.2.5. Studying non-standard employment outcomes

This study will take on a non-traditional approach in investigating the outcomes of non-standard employment. While previous research has often investigated the employment outcomes of non-standard employment by focusing on outcomes at one point in time or the duration until a certain employment outcome (often permanent employment) is reached (e.g. Booth et al., 2002; de Graaf-Zijl et al., 2011), we apply a multidimensional processual approach. In this approach, we take into account all events that occur after starting in a non-standard job, not only in terms of employment positions, but also in terms of income. This way, we can assess the quality of outcomes of non-standard employment based on the employment and income security workers experience in their careers.

19 In the early stages of doing this research, we tried to also create a typology of employer strategies using non-standard employment practices. This way, we hoped to be able to classify firms to one of the three main strategies. However, as no cluster solution explained more variance than the separate practices, this process was discontinued.

We do so by applying multichannel sequence analysis of the employment positions and incomes of all workers who start working in non-standard jobs as employees (Mattijssen & Pavlopoulos, 2019). This analysis results in a detailed typology that allows for classifying careers in terms of employment and income security. This typology can subsequently be related to both individual and firm characteristics to explain which non-standard employment strategies result in the most successful careers in terms of employment and income security, and which strategies make non-standard employment a trap for their employees.

5.3. Methods

5.3.1. Data

The data used for the construction of the typologies of non-standard employment are register data from the System of Social Statistical Datasets from Statistics Netherlands (*SSB*, Bakker et al., 2014). These data contain information about the employment positions and incomes of all individuals registered in the Netherlands. For our analysis of workers who start in non-standard employment, we specifically use a subset from these data that targets individuals who start to work in a fixed-term contract, on-call contract or temporary work agency contract in 2010. These are not necessarily first jobs, as a transition to these types of employment may occur later in the career as well. The main rule for inclusion in these data is to not have been employed in these types of non-standard employment in the three months before. These workers could be tracked from the moment of entering non-standard employment in 2010 until December 2016. At the outset, these data record careers of the individuals on a daily basis. As we do not require that much detail, we merged the data in such a way that we obtained monthly information per individual.

Mattijssen and Pavlopoulos (2019) have used the same data on the same population to develop a typology of non-standard employment trajectories for the 2007 cohort. To make our data for the 2010 cohort comparable to their approach, the following data selections are made. First, only individuals aged between 18 and 60 are included in the analysis. Student side-jobs, which are very common in the Dutch labour market, are excluded by selecting individuals who were not in education the moment they entered non-standard employment. Individuals who received old-age pension benefits, a surviving dependant's pension or annuities for at least 12 months in the observation period are excluded from the sample as well. The main difference with the data of Mattijssen and Pavlopoulos (2019) is that they had 96 months of data available, allowing them to track careers for eight years in total. In our case, we could observe the 2010 cohort until December 2016, limiting us to 72 months per individual. We exclude all individuals who could not be tracked for at least 72 months. This results in a final sample of 599,076 individuals.

For the selected individuals, we had information about their employment positions and incomes during all 72 months. For employment position, we distinguish between nine types: permanent contract, fixed-term contract, temporary work agency contract, on-call contract, self-employment, unemployed, welfare benefit, student and other. Income was aggregated into 13 categories as sequence analysis only works with categorical variables. We use a smaller range for the lower income groups and a large range for the higher income groups to create balanced brackets. Also, fluctuations of €250 likely have larger consequences at low levels of income than at higher levels of income.

5.3.2. Typology of non-standard employment trajectories

Our first step is to apply a multidimensional processual approach by creating a typology of non-standard employment trajectories that is representative of the full population of non-standard workers. By creating such a typology, we get an image of the overall types of careers for non-standard workers, that enables us to study, in the second step, how employers' strategies influence what type of careers workers have. To create the typology, we use multichannel sequence analysis (Gauthier et al., 2010; Pollock, 2007). Sequence analysis is a method that was originally used to study DNA sequences, but can also be used to study longitudinal phenomena. The main idea behind sequence analysis is to compare all sequences to one another and to calculate their similarity. Subsequently, based on these similarity scores, sequences can be clustered into groups, resulting in typologies.

Due to computational limitations, we could not analyse all 599,076 sequences simultaneously. Therefore, we randomly divide our sample into 14 subsamples of 42,791 or 42,792 individuals. For each subsample, we calculate the similarity of the sequences using the Hamming distance (Hamming, 1950). This distance measure is more sensitive to differences in timing than optimal matching, which is the standard distance measure in sequence analysis (Studer & Ritschard, 2016). Using the Hamming distance for instance prevents careers with late transitions from fixed-term to permanent employment (say, after 60 months) to be classified as similar to careers in which the transition from temporary to permanent employment occurs very early (after 6 months). After this, we clustered the sequences based on their similarity using the Ward clustering algorithm (Ward, 1963).

The results from these sequence and cluster analyses for the separate subsamples were compared qualitatively via the replication strategy suggested in Mattijssen & Pavlopoulos (2019) to arrive at a final typology that would be valid for all sequences. This strategy resulted in a typology of 17 clusters. More details on the technicalities of the sequence analysis, the replication strategy and the considerations we made in the process can be found in sections II.III to II.V in Technical Appendix II.

5.3.3. Non-standard employment practices

To create the variables measuring non-standard employment practices, we also used the System of Social Statistical Datasets from Statistics Netherlands. However, for this purpose we did not use the subset of workers who entered non-standard employment in 2010, but the full dataset of the working population in 2010 (n=8,527,549). For each individual, we had monthly information on their employment status and the (pseudonymized) firm they worked for in all months of 2010. If any change occurred throughout the year, for instance in employment status, this would also be registered. With this information, we could calculate firm level measures. Mathematical examples of the construction of the non-standard employment practices, as well as correlations between the four practices, can be found in Appendix 5A.

The first measure of firm practices that we use is the share of fixed-term contracts in the firm. To calculate this measure, we took into account that not all jobs last the entire year: some started halfway through the year, ended throughout the year, or were converted from fixed-term to permanent employment throughout the year. Therefore, the share of fixed-term employment in the firm was calculated as the ratio of the cumulative number of months in fixed-term employment among all workers in the firm divided by total months of employment of all workers in the firm. The same approach was used to calculate the second measure of firm practices, the share of on-call contracts in the firm. The firm-level mean share of fixed-term contracts is 33.1%, and the firm-level mean share of on-call contracts is 6.2%.

The third measure of firm practices is the transition rate from fixed-term to permanent employment. This was calculated as the ratio of the number of conversions of fixed-term to permanent contracts divided by the number of jobs with a fixed-term contract on the first record within that year. This transition rate has been likely underestimated, as we could not observe conversions that occurred from December 31st 2009 to January 1st 2010 and from December 31st 2010 to January 1st 2011. The firm-level mean transition rate is 8.6%.

The fourth and last measure of firm practices is excess mobility, which refers to mobility that is not necessary to establish the growth or shrinkage of the firm. Excess mobility was calculated as the ratio of the yearly net turnover rate in the firm – i.e. the number of inflows and outflows[20] minus the overall growth of the firm workforce – divided by the size of the total workforce of the firm. The firm-level mean excess mobility is 29.6%.

By constructing the indicators in this way, there is a small overlap (7%) between the population used to construct the non-standard employment practices and the population of non-standard workers whose trajectories are analysed. However, we think that this overlap is not problematic because the analytical sample is only a small part of the data used to calculate the non-standard employment practices, we track the careers of workers beyond 2010 and many workers also switch employers over time.

When these firm-level practices were calculated, we used the pseudonymized firm ID to link this information to the data on non-standard employees that was used to create the typology of non-standard employment trajectories and that is used in the explanatory analysis.

5.3.4. Analytical strategy

Before testing the relationship between the firm characteristics and workers' outcomes of non-standard employment, we made some further selections in our analytical sample. First, we only included workers in firms with at least 50 employees to ensure reliability of the non-standard employment practices. Second, we excluded workers who work for temporary work agencies as they are registered as workers of the temporary work agency and not of the firm for which they actually work. Thirdly, we excluded individuals who had missing values of any of the explanatory variables included in the analysis. In total, 278,974 individuals from 17,901 firms were included in the analysis.

5

To test the relationship between firm practices and workers' outcomes of non-standard employment, we used a multinomial logistic regression with the 17-cluster typology as the dependent variable. In the analysis, the standard errors are clustered at the firm level to account for the factor that we can have multiple workers from the same firm in our data.

The main independent variables in the analysis are the non-standard employment practices at the firm level: share of fixed-term contracts, share of on-call contracts, share of transitions to permanent employment and excess mobility. With the exception of the share of on-call contracts, these variables were operationalized as continuous. As many firms do not use on-call contracts (55.8% of firms), we decided to group this variable in five categories: no on-call contracts, up to 1% on-call contracts, between 1% and 5% on-call contracts, between 5% and 12.5% on-call contracts, and more than 12.5% on-call contracts. We also investigated whether any interactions between these practices improve the model fit. In the end, we included four interactions: between the share of fixed-term

20 Workers whose employment begins and ends within 2010 are only counted once.

contracts and the share of transitions to permanent employment, the share of fixed-term contracts and excess mobility, the share of fixed-term contracts and the share of on-call workers, and between excess mobility and the share of on-call workers.

To control for other relevant firm-level characteristics, we furthermore included the sector, the share of female workers in the firm, the share of high-paid workers, and a dummy for firms with over 250 employees as control variables. At the individual level, we controlled for gender, ethnicity (migrant/non-migrant background), education (4 levels), age and age squared. Descriptive statistics of all included variables can be found in Appendix 5B.

5.3.5. Dominance analysis

Next to assessing the effects of the non-standard employment practices, it is also relevant to see how the predictive power of these practices compares to the predictive power of individual characteristics and other firm characteristics. To find out, we run a dominance analysis using the *domin* package for Stata (Luchman, 2014). A dominance analysis compares the relative importance of the explanatory variables in the analysis by running models with all possible combinations of the independent variables and assessing how often the variables have more predictive power than the others.

A complete dominance analysis for our model, excluding the interaction effects, would require the analysis of 2^{13}-1=8191 models. Such an analysis was not feasible. Furthermore, we are more interested in how variable sets compare to one another in their explanatory power. Therefore, we run the dominance analysis with three main sets of variables, limiting the number of required analyses to 2^3-1=7 models. The three main sets of variables are individual characteristics (gender, level of education, ethnicity, age and age^2), firm characteristics (share of women in the firm, share of high-paid workers in the firm, sector and firm size), and the non-standard employment practices (share of fixed-term contracts, share of on-call contracts, share of transitions from fixed-term to permanent and excess mobility). As interaction effects should not be included in models without their main effects, the interactions between the non-standard employment practices are not included in the dominance analysis. The main model fit indicator we use to compare the strength of the variable sets is the McFadden R^2.

Additionally, we run a separate dominance analysis to assess which of the firm characteristics contributes most to the model. In this dominance analysis, we include the individual characteristics and other firm characteristics as sets, while the practices are included separately. The total number of variables/sets in this analysis is thus 6, which means that 2^6-1=63 models are run. With the same approach, we also investigate which of the variables within the sets of individual characteristics and firm characteristics contribute most to the model.

5.4. Results

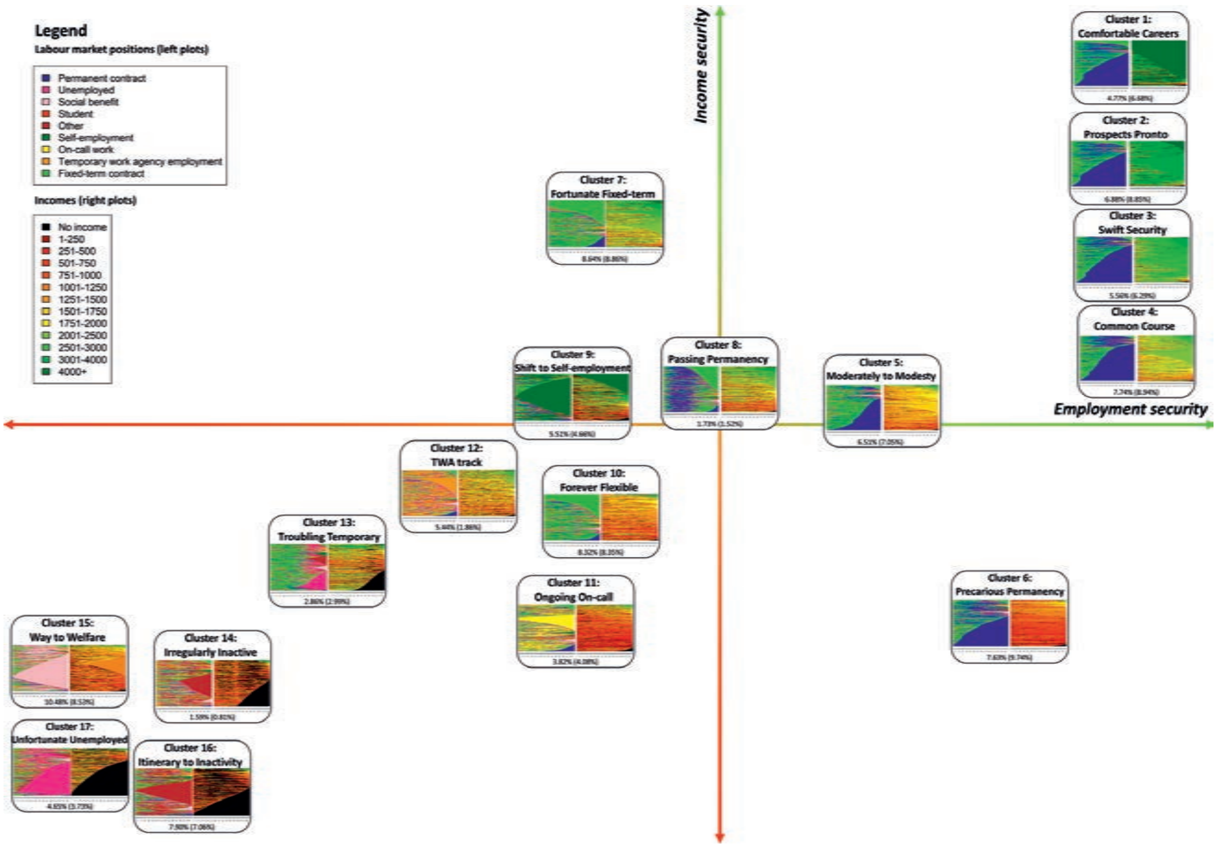
5.4.1. Typology of non-standard employment careers

The sequence analysis resulted in a typology of 17 career types that vary in the level of employment and income security they provide the workers. Each cluster is given a name that reflects the type of careers that can be found in that cluster. To ease interpretability of the typology, we have placed the clusters on a grid, stratifying the clusters horizontally based on their employment security, and vertically based on their income security (Figure 5.1). The placement of the clusters on the grid is done qualitatively: there is no hard measure of employment and income security and the distance between clusters should not be seen as absolute. We did, however, take into account several quantitative characteristics to determine the placement of the clusters. For employment security, we took into account the percentage of time spent in employment, the percentage of time spent in permanent employment and the average duration until permanent employment. For income security, we took into account the mean within trajectory income and the average within trajectory income standard deviation. Cluster scores on these indicators can be found in Table 5B.3 in Appendix 5B.

On the top right of the grid, we find career types that offer high levels of employment security, and can be seen as the ideal typical *stepping stone* careers. In these clusters, workers make the transition to permanent employment quite quickly, albeit a bit slower in *Moderately to Modesty*. The highest levels of income security can be found in *Comfortable Careers*, with income levels around €3000-€4000 monthly, while *Moderately to Modesty* and *Common Course* have relatively lower, but still decent levels of income security at around €2000 monthly. Combined, the five clusters in this quadrant contain 31.4% of the workers who entered flexible employment in 2010, and 37.8% of the workers in our analytical sample.

On the opposite side of the grid, in the lower left quadrant, we find the clusters that are characterized by low levels of both employment and income security. These clusters can be seen as the ideal typical *trap*-careers. First of all, we find four clusters that are characterized by non-employment. The workers in *Way to Welfare* will spend a large share of their trajectory in some kind of welfare benefit, while workers in *Unfortunate Unemployed* end up unemployed, generally without any benefits. The workers in *Itinerary to Inactivity* end up leaving the labour market for a longer period of time, for instance for taking on care tasks. The same holds for workers in *Irregularly Inactive*, but they make this transition a bit later in their trajectories. Together, these four clusters combined contain 24.4% of all workers, and 20.1% of the final sample.

Figure 5.1: Typology of non-standard employment careers[1]



[1] The size of the cluster in the population and in the final analytical sample (in brackets) are presented under the plots.

However, this quadrant also contains four clusters with low levels of employment and income security in which workers are mostly employed. In *Ongoing On-call*, workers spend most of their trajectory in on-call employment, earning relatively low and unstable incomes. The same holds for the *Temporary Work Agency (TWA) Track*, but then for working in temporary work agency jobs. There are also two clusters in which workers spend most of their trajectories in fixed-term employment. In *Forever Flexible*, this fixed-term employment is relatively stable, but the incomes are on the lower side. In *Troubling Temporary*, the fixed-term employment is less stable, with workers often switching between fixed-term employment, other types of flexible employment and non-employment. As a result, the incomes are less stable as well. Together, these four clusters contain 20.4% of all workers, and 17.3% of the workers in the analytical sample.

Next to these ideal typical *stepping stone* and *trap* clusters, we also encounter a couple of clusters that deviate from the traditional dichotomy. On the bottom right side of the quadrant, we for instance find a cluster that combines relatively high levels of employment security with relatively low levels of income security: *Precarious Permanent*. In this cluster, workers make the transition to permanent employment at some point in their trajectories, while earning stable but low incomes of around €750-€1000 monthly. This cluster shows that a transition to permanent employment does not necessarily equate a good career in all respects. This cluster contains 7.6% of the total sample of non-standard workers, and 9.7% of the final sample.

On the opposite, upper left side of the grid, we see the exact opposite with the cluster *Fortunate Fixed-term*. In this cluster, workers mostly remain in fixed-term employment throughout their trajectories. In previous research, these workers would have been classified as precarious. However, when looking at their incomes, these are generally high, stable and often increasing. In this respect, these workers cannot really be classified as precarious, showing that fixed-term employment can also be a good outcome for some. This cluster contains 8.6% of all non-standard workers and 8.9% of the analytical sample.

Two clusters remain harder to classify into one of the quadrants, as they show a mixed image. First, there is the cluster *Shift to Self-employment* in which workers transition to self-employment. By definition, self-employment does not ensure employment security as the self-employed need to ensure their own employment. The extent to which this works, varies per self-employed. Next to this, we see that the income levels in this cluster are extremely varied: a significant share of these self-employed earn very high incomes of €4000 and over, while another significant share has a very low and unstable income. Therefore, this cluster is located in the middle of the grid. This cluster contains 5.5% of workers and 4.7% of the final sample.

Second and finally, the cluster *Passing Permanency* shows an interesting career trajectory. In this cluster, workers make the transition to permanent employment quite quickly, but after some time return to fixed-term employment. The incomes in this cluster are mixed, and also the income development varies: some experience income increases while others experience income decreases. This may be an indication that the transition from permanent to fixed-term employment is a voluntary transition for some, while it may be an involuntary transition for some. Therefore, this cluster is placed in the middle of the grid as well. This cluster contains 1.7% of the workers and 1.5% of our analytical sample.

5.4.2. Non-standard employment practices and non-standard employment trajectories

To enhance interpretability of our multinomial logistic regression, and the interaction effects in particular, we present the results using average marginal effects (Mize, 2019). These numbers can be interpreted as the percentage-point change in the probability of experiencing one of the 17 outcomes of the dependent variable as a result of one unit increase of the independent variable. The results for the non-standard employment practices and their interactions can be found in Table 5.2, the full results including all control variables can be found in Table 5C.1 in Appendix 5C.

The results first of all show that a higher share of fixed-term contracts in a firm results in career types characterized by lower levels of employment security. The higher the share of fixed-term contracts in a firm, the more likely workers are to experience a *Fortunate Fixed-term* or *Forever Flexible* career type, characterized by long-term fixed-term contracts with respectively higher and lower levels of income security. At the same time, a higher share of fixed-term workers decreases the chance to experience *Precarious Permanent* careers, characterized by high levels of employment security and medium to lower levels of income security, as well as the chance to experience a *Passing Permanent* career. At the same time, the probability of experiencing a *Troubling Temporary* career increases with the share of fixed-term workers. A higher share of fixed-term workers in the firm however decreases the chance of taking the *Itinerary to Inactivity*, becoming *Irregularly Inactive* or *Unfortunate Unemployed*. It also decreases the chance of ending up in an *Ongoing On-call* career.

The effect of the share of on-call contracts depends on the how many on-call contracts are used. In firms with up to 1% on-call contracts, the outcomes of workers are quite decent, with increased probabilities of experiencing *Prospects Pronto, Swift Secure* or *Fortunate Fixed-term* careers and decreased chances of experiencing *Way to Welfare, Itinerary to Inactivity* and *Unfortunate Unemployed* careers, compared to firms with no on-call contracts. However, as the share of on-call contracts in the firm increases, the career outcomes become more precarious. In firms with over 12.5% on-call contracts, the probability to experience a *Comfortable Career, Prospects Pronto* or a *Fortunate Fixed-term* career decreases, while the probability of having an *Ongoing On-call* career, to make the *Shift to Self-employment* or to become *Irregularly Inactive* increases. However, a high share of on-call contracts does protect against the *Way to Welfare, Forever Flexible* and *Troubling Temporary* careers. Generally, higher shares of on-call work thus result in lower levels of employment and income security.

The transition rate from fixed-term to permanent employment also affects the employment security of workers, but the effects are largely opposite to the effect of the share of fixed-term contracts. The higher the share of transitions from fixed-term to permanent employment in the firm, the more likely it is for individual workers to have a career with higher levels of employment and income security, such as *Comfortable Careers*, *Prospects Pronto, Swift Security* and *Common Course*. At the same time, a high transition rate from fixed-term to permanent protects against careers characterized by precarious non-standard employment, such as *Forever Flexible* and *Troubling Temporary*, and against careers ending in welfare benefits (*Way to Welfare*) and long-term inactivity (*Itinerary to Inactivity*). Workers are also more likely to have *Precarious Permanent* careers, and also more likely to experience *Passing Permanency*. Summing up, the more workers in a firm make the shift from fixed-term to permanent employment, the more likely non-standard workers are to make that transition themselves too.

Finally, excess mobility in a firm also has very interesting effects on the careers of workers in the firm. Not only do higher levels of excess mobility decrease the chance of having careers with high levels of employment and income security, they also decrease the chance of having a *Fortunate Fixed-term* or *Forever Flexible* career. Higher levels of excess mobility do strongly increase the chance of workers to experience a career type characterized by non-employment, in particular *Way to Welfare* and *Itinerary to Inactivity*. We also see that higher levels of excess mobility also increase the probability of the *Temporary Work Agency Track*, *Passing Permanency* and to make the *Shift to Self-employment*. Overall, firms with high levels of excess mobility are likely to result in low levels of employment and income security for workers.

Table 5.2: Marginal effects from the multinomial logistic regression

Cluster	Comfortable Careers	Prospects Pronto	Swift Security	Common Course	Moderately to Modesty	Precarious Permanent	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	Ongoing On-call	TWA Track	Troubling Temporary	Irregularly Inactive	Way to Welfare	Itinerary to Inactivity	Unfortunate Unemployed
Main effects non-standard employment practices																	
Share of fixed-term contracts	0.009	0.010	-0.005	-0.016	0.045***	-0.040*	0.085***	-0.010**	-0.024	0.060***	-0.035***	-0.003	0.017***	-0.007***	-0.026	-0.047***	-0.015*
	(0.008)	(0.011)	(0.009)	(0.012)	(0.006)	(0.018)	(0.012)	(0.003)	(0.014)	(0.010)	(0.008)	(0.003)	(0.002)	(0.002)	(0.021)	(0.011)	(0.006)
Share of on-call contracts (ref: 0)																	
0-1	0.636	0.724*	0.707*	0.105	0.229	-2.494**	2.904***	-0.028	-0.722**	0.828*	0.028	0.074	-0.025	0.143	-1.948***	-0.543*	-0.619**
	(0.331)	(0.327)	(0.275)	(0.331)	(0.409)	(0.878)	(0.578)	(0.080)	(0.243)	(0.408)	(0.136)	(0.158)	(0.163)	(0.078)	(0.491)	(0.248)	(0.196)
1-5	-0.771**	0.064	0.806**	1.349**	-0.056	-1.830*	1.007**	0.086	0.425*	1.272	1.085***	-0.434***	-0.058	0.050	-1.936***	-0.323	-0.735***
	(0.292)	(0.273)	(0.249)	(0.400)	(0.346)	(0.789)	(0.371)	(0.111)	(0.210)	(0.663)	(0.181)	(0.107)	(0.193)	(0.077)	(0.473)	(0.272)	(0.130)
5-12,5	-0.977**	-0.143	0.805**	1.526***	-0.078	-1.765*	0.519	0.031	0.868***	-0.731*	3.321***	-0.490***	-0.340*	0.373***	-2.429***	-0.468	-0.022
	(0.298)	(0.323)	(0.257)	(0.360)	(0.353)	(0.839)	(0.422)	(0.103)	(0.238)	(0.332)	(0.343)	(0.112)	(0.158)	(0.080)	(0.586)	(0.275)	(0.207)
12,5+	-1.752***	-2.165***	-0.230	0.391	-1.487***	-1.089	-1.141**	0.133	1.447***	-1.787***	9.704***	0.107	-0.918***	0.808***	-2.184***	-0.074	0.238
	(0.382)	(0.367)	(0.312)	(0.418)	(0.352)	(0.940)	(0.425)	(0.115)	(0.283)	(0.416)	(1.185)	(0.154)	(0.181)	(0.099)	(0.397)	(0.263)	(0.148)
Excess mobility	-0.023*	-0.058***	-0.060***	-0.087***	-0.053***	-0.006	-0.074***	0.012**	0.083***	-0.053***	-0.002	0.034***	-0.003	0.014***	0.133***	0.093***	0.052***
	(0.011)	(0.015)	(0.009)	(0.011)	(0.012)	(0.019)	(0.012)	(0.004)	(0.017)	(0.010)	(0.009)	(0.006)	(0.004)	(0.002)	(0.016)	(0.018)	(0.004)
Transition rate	0.038***	0.089***	0.068***	0.116***	0.021	0.113***	-0.017	0.018***	-0.054	-0.118**	-0.068**	-0.006	-0.008	-0.007	-0.105**	-0.077**	-0.001
	(0.010)	(0.014)	(0.010)	(0.015)	(0.022)	(0.024)	(0.041)	(0.004)	(0.028)	(0.038)	(0.022)	(0.011)	(0.009)	(0.005)	(0.037)	(0.025)	(0.009)
Interactions between non-standard employment practices																	
Share of fixed-term contracts * Excess mobility																	
0	0.025	-0.002	-0.033*	-0.068***	0.030*	-0.067**	0.130***	-0.014***	-0.018	0.100**	-0.032*	-0.005**	0.025***	-0.005**	-0.022	-0.030***	-0.013
	(0.013)	(0.015)	(0.014)	(0.018)	(0.015)	(0.022)	(0.018)	(0.002)	(0.012)	(0.036)	(0.014)	(0.002)	(0.005)	(0.002)	(0.020)	(0.008)	(0.009)
20	0.012	0.008	-0.012	-0.033*	0.040***	-0.053**	0.105***	-0.012***	-0.024	0.081***	-0.034**	-0.006**	0.021***	-0.007***	-0.029	-0.042***	-0.015
	(0.009)	(0.012)	(0.010)	(0.014)	(0.009)	(0.019)	(0.013)	(0.003)	(0.015)	(0.022)	(0.010)	(0.002)	(0.004)	(0.002)	(0.022)	(0.010)	(0.008)
30	0.006	0.013	-0.003	-0.018	0.044***	-0.045*	0.092***	-0.011**	-0.027	0.072***	-0.035***	-0.005*	0.019***	-0.007***	-0.031	-0.047***	-0.015*
	(0.007)	(0.012)	(0.009)	(0.013)	(0.007)	(0.018)	(0.012)	(0.003)	(0.016)	(0.016)	(0.009)	(0.002)	(0.003)	(0.002)	(0.023)	(0.011)	(0.007)
40	0.001	0.017	0.005	-0.005	0.046***	-0.035	0.079***	-0.008*	-0.029	0.062***	-0.036***	-0.004	0.017***	-0.008***	-0.033	-0.052***	-0.015*
	(0.007)	(0.011)	(0.008)	(0.011)	(0.006)	(0.019)	(0.011)	(0.004)	(0.016)	(0.010)	(0.008)	(0.003)	(0.003)	(0.002)	(0.023)	(0.012)	(0.006)
60	-0.008	0.021*	0.015*	0.013	0.047***	-0.014	0.054***	-0.002	-0.029	0.043***	-0.037***	0.000	0.011***	-0.009**	-0.032	-0.061***	-0.013**
	(0.008)	(0.011)	(0.006)	(0.009)	(0.005)	(0.020)	(0.010)	(0.004)	(0.017)	(0.006)	(0.009)	(0.005)	(0.003)	(0.003)	(0.023)	(0.015)	(0.004)
80	-0.015	0.021*	0.018**	0.022**	0.042***	0.006	0.032**	0.005	-0.024	0.024*	-0.036**	0.009	0.005	-0.009	-0.027	-0.066**	-0.009
	(0.010)	(0.010)	(0.006)	(0.007)	(0.007)	(0.021)	(0.010)	(0.004)	(0.017)	(0.012)	(0.013)	(0.007)	(0.004)	(0.006)	(0.025)	(0.020)	(0.008)

Table 5.2: *(continued)*

Share of fixed-term contracts * Transition rate																	
0	0.002	-0.007	-0.023**	-0.052***	0.031***	-0.045**	0.069***	-0.009***	-0.005	0.079***	-0.018*	-0.001	0.016***	-0.001	0.002	-0.023***	-0.013**
	(0.006)	(0.008)	(0.007)	(0.011)	(0.006)	(0.014)	(0.009)	(0.002)	(0.006)	(0.014)	(0.007)	(0.002)	(0.002)	(0.002)	(0.012)	(0.006)	(0.005)
5	0.005	0.000	-0.015*	-0.036**	0.042***	-0.043**	0.083***	-0.009***	-0.015	0.067***	-0.027***	-0.002	0.017***	-0.004*	-0.015	-0.035***	-0.013*
	(0.006)	(0.009)	(0.008)	(0.011)	(0.006)	(0.015)	(0.009)	(0.003)	(0.010)	(0.011)	(0.007)	(0.003)	(0.002)	(0.002)	(0.017)	(0.008)	(0.005)
10	0.007	0.007	-0.006	-0.019	0.051***	-0.041*	0.097***	-0.009**	-0.023	0.055***	-0.036***	-0.003	0.019***	-0.006***	-0.031	-0.047***	-0.014*
	(0.007)	(0.011)	(0.009)	(0.013)	(0.007)	(0.017)	(0.016)	(0.003)	(0.013)	(0.009)	(0.008)	(0.003)	(0.003)	(0.002)	(0.021)	(0.011)	(0.006)
15	0.010	0.014	0.002	0.000	0.059***	-0.040	0.108***	-0.010**	-0.032	0.043***	-0.044***	-0.004	0.019***	-0.008***	-0.046	-0.058***	-0.016*
	(0.008)	(0.014)	(0.011)	(0.015)	(0.009)	(0.021)	(0.025)	(0.004)	(0.017)	(0.010)	(0.008)	(0.004)	(0.004)	(0.002)	(0.025)	(0.014)	(0.008)
20	0.013	0.022	0.012	0.021	0.066***	-0.041	0.118**	-0.011*	-0.039*	0.032**	-0.051***	-0.006	0.019***	-0.010***	-0.059*	-0.068***	-0.017
	(0.010)	(0.018)	(0.014)	(0.019)	(0.012)	(0.025)	(0.034)	(0.004)	(0.019)	(0.011)	(0.008)	(0.005)	(0.005)	(0.002)	(0.029)	(0.016)	(0.009)
25	0.015	0.029	0.021	0.042	0.072***	-0.042	0.126**	-0.012*	-0.046*	0.021	-0.056***	-0.008	0.019***	-0.012***	-0.072*	-0.078***	-0.020
	(0.011)	(0.022)	(0.017)	(0.024)	(0.015)	(0.030)	(0.044)	(0.005)	(0.021)	(0.012)	(0.008)	(0.006)	(0.005)	(0.002)	(0.031)	(0.018)	(0.010)
30	0.017	0.036	0.030	0.064*	0.076***	-0.046	0.133*	-0.013*	-0.052*	0.011	-0.061***	-0.009	0.018**	-0.014***	-0.082*	-0.086***	-0.022
	(0.012)	(0.026)	(0.020)	(0.029)	(0.017)	(0.036)	(0.054)	(0.006)	(0.023)	(0.013)	(0.008)	(0.006)	(0.006)	(0.002)	(0.033)	(0.020)	(0.012)
Share of fixed-term contracts * Share of on-call contracts																	
0-1	0.009	-0.004	-0.011	0.000	0.045***	-0.045*	0.077***	-0.009**	-0.025	0.064**	-0.010**	0.001	0.014***	-0.004*	-0.033	-0.052***	-0.016*
	(0.009)	(0.014)	(0.010)	(0.013)	(0.008)	(0.022)	(0.014)	(0.003)	(0.016)	(0.021)	(0.003)	(0.003)	(0.004)	(0.001)	(0.027)	(0.013)	(0.008)
1-5	0.004	0.072**	0.037*	-0.016	0.068***	-0.107**	0.162***	-0.009	-0.039*	0.057**	-0.035***	-0.007	0.015**	-0.015***	-0.071**	-0.093***	-0.021**
	(0.011)	(0.023)	(0.015)	(0.024)	(0.017)	(0.033)	(0.022)	(0.005)	(0.018)	(0.018)	(0.006)	(0.006)	(0.005)	(0.004)	(0.023)	(0.018)	(0.007)
5-12,5	0.005	-0.013	-0.018	-0.024	0.039**	-0.042	0.062**	-0.014*	-0.016	0.097***	-0.032**	-0.008	0.041***	-0.003	-0.046	-0.017	-0.014
	(0.013)	(0.017)	(0.015)	(0.024)	(0.012)	(0.022)	(0.020)	(0.006)	(0.014)	(0.022)	(0.011)	(0.005)	(0.009)	(0.003)	(0.029)	(0.011)	(0.007)
12,5+	0.032*	-0.010	-0.026	-0.040	0.048***	-0.032	0.060***	-0.017**	0.013	0.069***	-0.083***	-0.007	0.016**	-0.008	0.024	-0.024	-0.015
	(0.014)	(0.016)	(0.014)	(0.021)	(0.013)	(0.021)	(0.016)	(0.005)	(0.013)	(0.011)	(0.022)	(0.004)	(0.006)	(0.005)	(0.022)	(0.015)	(0.009)
Excess mobility * Share of on-call contracts																	
0-1	-0.024	-0.040*	-0.049***	-0.093***	-0.074***	-0.034	-0.065***	0.013**	0.085***	-0.066**	0.025***	0.032***	-0.006	0.012***	0.134***	0.100***	0.048***
	(0.013)	(0.018)	(0.012)	(0.013)	(0.020)	(0.026)	(0.014)	(0.004)	(0.019)	(0.023)	(0.004)	(0.007)	(0.006)	(0.002)	(0.018)	(0.021)	(0.004)
1-5	-0.047*	-0.125***	-0.113***	-0.096**	-0.094***	0.110*	-0.183***	0.017*	0.090***	-0.069*	0.046***	0.059***	-0.006	0.031***	0.184***	0.138***	0.059***
	(0.020)	(0.033)	(0.023)	(0.028)	(0.024)	(0.044)	(0.034)	(0.007)	(0.022)	(0.030)	(0.010)	(0.008)	(0.008)	(0.005)	(0.025)	(0.024)	(0.008)
5-12,5	-0.039	-0.072**	-0.041	-0.098**	-0.036*	0.047	-0.070**	0.015	0.082**	-0.090**	-0.003	0.030***	-0.032*	0.006	0.183***	0.073***	0.044***
	(0.023)	(0.025)	(0.023)	(0.031)	(0.016)	(0.028)	(0.025)	(0.009)	(0.026)	(0.027)	(0.015)	(0.006)	(0.015)	(0.004)	(0.031)	(0.017)	(0.010)
12,5+	0.027	-0.058*	-0.075***	-0.069*	-0.026	-0.009	-0.034	0.006	0.064***	-0.046**	-0.042	0.011	0.013	0.010	0.086***	0.067*	0.074***
	(0.024)	(0.024)	(0.021)	(0.027)	(0.019)	(0.031)	(0.025)	(0.008)	(0.017)	(0.017)	(0.024)	(0.010)	(0.009)	(0.006)	(0.023)	(0.027)	(0.014)

5.4.3. Strategies: the interplay between non-standard employment practices

Though we have seen the average effects of the four separate practices, for determining the effect of non-standard employment strategies, the interplay between these practices is most relevant. For interpretability and to make the connection to the ideal-typical non-standard employment strategies, we have calculated adjusted predicted probabilities at representative values of the practices for each of the three strategies to illustrate how the strategies affect the outcomes of workers in these firms. These values are in line with the expectations presented in Table 5.1. For firms with screening strategies, we have chosen 10% of fixed-term contracts, 0% of on-call contracts, a 30% transition rate and 20% excess mobility. For firms with adaptability practices, we also limited the share of fixed-term contracts to 10%, chose a share of on-call contracts between 1% and 5%, a 0% transition rate and 40% excess mobility. For firms with cost reduction strategies, we chose a 80% share of fixed-term contracts, a 0% transition rate and 80% excess mobility. We did not specify the share of on-call workers.[21]

The predicted probabilities for the ideal types can be found in Figure 5.2. The predicted probabilities are presented per cluster, and we placed the plots on the same grid that was used to plot the typology of outcomes of non-standard employment. In the plots, the green bars on the left indicate the predicted probabilities for the screening strategy, the yellow bars in the middle the predicted probabilities for the adaptability strategy, and the red bars at the right those for the cost reduction strategy. The blue horizontal line shows the overall predicted probability of the workers to experience that career path. For each probability, a 95%-confidence interval is plotted as well. The exact predicted probabilities can be found in Table 5C.2 in Appendix 5C.

Starting with firms with screening strategies, we see that workers in these firms are more likely to have careers characterized by high levels of employment security. For instance, they are more likely to experience *Comfortable Careers, Prospects Pronto,* but also *Precarious Permanent* careers, and less likely to experience *Ongoing On-call* or *TWA Track* careers. They also have lower probabilities to experience careers characterized by non-employment, such as *Itinerary to Inactivity*, *Way to Welfare* or *Unfortunate Unemployed*.

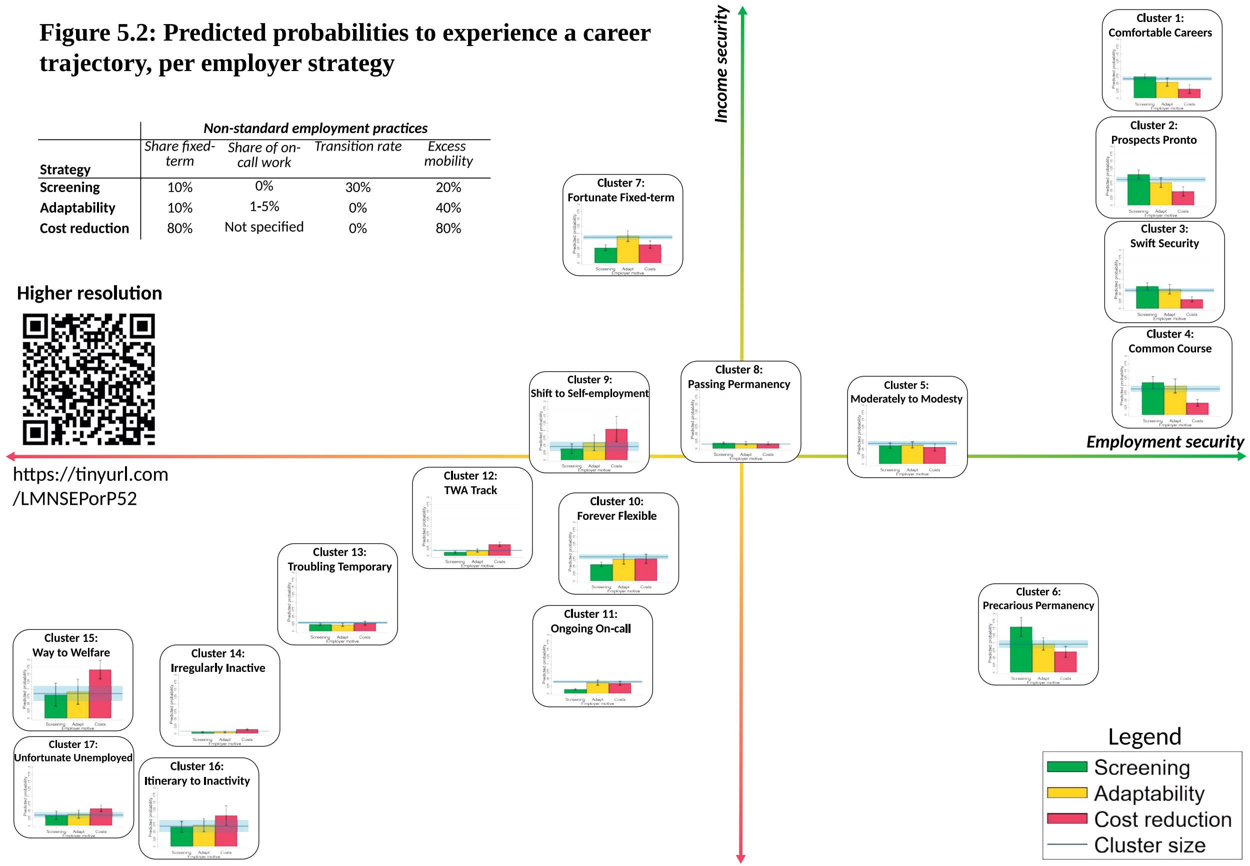
21 Predicted probabilities for 222 other combinations of the non-standard employment practices are available upon request. The three chosen combinations are also plotted in the scatterplot in Figure 5B.1 in Appendix 5B.

Figure 5.2: Predicted probabilities to experience a career trajectory, per employer strategy

Strategy	Share fixed-term	Share of on-call work	Transition rate	Excess mobility
	Non-standard employment practices			
Screening	10%	0%	30%	20%
Adaptability	10%	1-5%	0%	40%
Cost reduction	80%	Not specified	0%	80%

Higher resolution

https://tinyurl.com
/LMNSEPorP52



Note: This graph shows the predicted probabilities of experiencing any of the 17 career outcomes for three ideal typical strategies (bars), constructed using combinations of scores on the non-standard employment practices, as well as the overall predicted probability of experiencing the career types (horizontal line). 95% confidence intervals included.

In contrast, workers in firms with cost reduction strategies are more likely to have careers with lower levels of employment and income security, and in particular careers characterized by non-employment such as *Way to Welfare*, *Itinerary to Inactivity* and *Unfortunate Unemployed*. They are also significantly less likely to have careers with high levels of employment and income security, such as *Comfortable Careers, Prospects Pronto* or *Swift Security*, and more likely to experience a *TWA Track* and to make the *Shift to Self-employment*.

Workers in firms with adaptability strategies hold a middle ground between the screening and cost reduction strategies. On the one hand they have lower levels of employment and income security than workers from firms with screening strategies, for instance due to lower probabilities to have a *Comfortable Career* or *Prospects Pronto* and higher chances to have an *Ongoing On-call* or *TWA Track* career. They are also more likely to have a *Fortunate Fixed-term* career, that combines high levels of income security with lower levels of employment security. On the other hand, they are equally likely as workers from firms with screening strategies, and hence significantly less likely than workers from firms with cost reduction strategies, to have careers characterized by non-employment, such as *Way to Welfare*, *Unfortunate Unemployed* or *Itinerary to Inactivity*. This indicates that the scarring effect of non-standard employment may indeed be weaker for workers in firms with adaptability strategies.

Some final interesting findings are those where workers from the three different types of strategies do not differ significantly from each other. This is the case for *Moderately to Modesty*, *Passing Permanency* and *Troubling Temporary*. This shows that the effect is not particular linear: screening strategies do not protect against all careers with low levels of employment and income security, such as *Troubling Temporary*, while cost reduction strategies do not preclude careers with higher levels of employment security either.

5.4.4. What matters most in predicting career trajectories: a dominance analysis

To assess which of the three variable sets explained most variance in the outcomes of non-standard employment, we ran a dominance analysis. The results of the dominance analysis can be found in Table 5.3. The analysis shows that the individual characteristics have the highest explanatory power: including individual characteristics to the model improve the McFadden R^2 by 6.4 percentage points (pp), almost half of the total predictive power. The other firm characteristics further improved the model by 4.1 pp. Finally, the non-standard employment practices significantly contributed to the model as well. Including the non-standard employment practices to the model improved the McFadden R^2 by 2.5 pp. This amounts to 18.9% of the total explanatory power of all sets combined, showing that employer strategies play an important role in the outcomes of non-standard employment and should definitely not be neglected.

Table 5.3: Dominance analyses

	Dominance	Standardized Dominance	Conditional dominance						
Dominance analysis of three variable sets			1 set	2 sets	3 sets				
Individual characteristics	6.40%	49.41%	8.43%	5.95%	4.81%				
Firm characteristics	4.10%	31.66%	6.65%	3.65%	2.00%				
Non-standard employment practices	2.45%	18.91%	4.01%	2.00%	1.34%				
Overall fit statistic	12.94%								
Dominance analysis of the four non-standard employment practices[a]			1 set	2 sets	3 sets	4 sets	5 sets	6 sets	
Individual characteristics	6.34%	48.97%	8.43%	7.29%	6.45%	5.79%	5.25%	4.81%	
Firm characteristics	3.96%	30.60%	6.65%	5.19%	4.10%	3.25%	2.57%	2.00%	
Excess mobility[b]	1.02%	7.90%	2.29%	1.45%	0.94%	0.64%	0.46%	0.36%	
% on-call contracts	0.93%	7.21%	1.58%	1.19%	0.93%	0.74%	0.62%	0.53%	
% fixed-term contracts	0.45%	3.46%	1.13%	0.62%	0.36%	0.24%	0.18%	0.15%	
% transitions fixed-term to permanent	0.24%	1.86%	0.58%	0.32%	0.20%	0.15%	0.11%	0.09%	
Overall fit statistic	12.94%								
Dominance analysis of the firm characteristics			1 set	2 sets	3 sets	4 sets	5 sets	6 sets	
Individual characteristics	6.15%	47.55%	8.43%	7.05%	6.10%	5.47%	5.06%	4.81%	
Non-standard employment practices	2.29%	17.72%	4.01%	2.91%	2.21%	1.78%	1.51%	1.33%	
% high-paid workers[c]	1.78%	13.74%	3.64%	2.53%	1.75%	1.23%	0.87%	0.64%	
Sector	1.56%	12.08%	3.26%	2.16%	1.45%	1.03%	0.80%	0.68%	
% female workers in firm	1.04%	8.03%	2.29%	1.53%	1.02%	0.67%	0.44%	0.28%	
Firm size	0.11%	0.88%	0.21%	0.17%	0.11%	0.08%	0.06%	0.05%	
Overall fit statistic	12.94%								
Dominance analysis of individual characteristics			1 set	2 sets	3 sets	4 sets	5 sets	6 sets	7 sets
Firm characteristics	4.13%	31.90%	6.65%	5.68%	4.78%	3.97%	3.24%	2.58%	2.00%
Level of education[d]	2.65%	20.51%	3.60%	3.22%	2.87%	2.57%	2.32%	2.09%	1.90%
Non-standard employment practices	2.44%	18.88%	4.01%	3.33%	2.75%	2.26%	1.86%	1.55%	1.33%
Gender	1.83%	14.16%	2.49%	2.27%	2.05%	1.82%	1.61%	1.40%	1.19%
Ethnicity[d]	0.76%	5.88%	1.01%	0.90%	0.81%	0.73%	0.67%	0.62%	0.57%
Age	0.64%	4.93%	0.61%	0.63%	0.63%	0.64%	0.64%	0.65%	0.67%
Age^2	0.48%	3.74%	0.55%	0.51%	0.48%	0.46%	0.46%	0.46%	0.47%
Overall fit statistic	12.94%								

[a] In this dominance analysis, the individual characteristics and firm characteristics are included as sets, while the non-standard employment practices are included separately in the models.
[b] For practically all variables holds that the ranking of variables on the basis of general dominance means that they completely dominate the lower-ranking variables in all models. The only exceptions are excess mobility and % on-call contracts. For these variables holds that excess mobility *generally* dominates % on-call contracts, meaning that in some models, % on-call contracts was dominant over excess mobility, but on average, excess mobility was more dominant than % on-call contracts.
[c] For practically all variables holds that the ranking of variables on the basis of general dominance means that they completely dominate the lower-ranking variables in all models. The only exceptions are % high paid workers and sector. For these variables holds that the share of high-paid workers *generally* dominates sector.
[d] For practically all variables holds that the ranking of variables on the basis of general dominance means that they completely dominate the lower-ranking variables in all models. The only exceptions are ethnicity and age, where ethnicity *generally* dominates age, and level of education and the non-standard employment practices, where level of education *generally* dominates the non-standard employment practices.

To see which of the four non-standard employment practices contributed most to the prediction of career types, we also ran a separate dominance analysis. This analysis shows that, of the four practices, excess mobility improves the McFadden R^2 most (1 pp), followed by the share of on-call contracts (0.9 pp). The share of fixed-term contracts (0.45 pp) and the transition rate from fixed-term to permanent employment (0.24 pp) contribute least to the model. These results differ slightly from the first dominance analysis, as the correlation between the practices as a set with the other variable sets likely differs from the correlation between the practices separately with the other variable sets.

Looking in more detail into the other variable sets, we see that of the individual characteristics, gender contributes most to the model (1.8 pp), followed by ethnicity (0.8 pp), age (0.6 pp) and age^2 (0.5 pp). Of the firm characteristics, we see that the share of high-paid workers and the sector contribute most to the models (1.8 pp and 1.6 pp respectively), followed by the share of female workers in the firm (1.0 pp). Firm size in contrast contributes least to the model (0.1 pp).

5.5. Conclusion

The aim of this chapter was to investigate to what extent employers' non-standard employment strategies affect the career outcomes of workers who start working in non-standard employment in those firms. Employers' strategies are key mechanisms in the main scenarios predicting the employment outcomes of non-standard employment for workers, the *stepping stone* scenario and the *trap* scenario. We distinguish three basic strategies of employers in using non-standard employment: screening, adaptability and cost reduction. It was expected that workers in firms with screening strategies experience better career trajectories than workers in firms with adaptability or cost reduction strategies. Using employment register data, we could assign the careers of all workers in the Netherlands who started working in a non-standard employment contract in 2010 in a 17-category typology with multichannel sequence analysis, as well as create firm-level aggregate indicators of non-standard employment practices that reflect employers' strategies: the share of fixed-term contracts and on-call contracts, the transition rate from fixed-term to permanent employment and excess mobility.

Our analysis confirms the crucial role that employers' strategies play in determining the outcomes of non-standard employment of workers. Next to individual level and firm level characteristics, these strategies have an independent effect on whether non-standard employment functions as stepping stone or as a trap in the subsequent years in workers' careers. These strategies mostly influence the employment security, but not (directly) the income security, of the careers of their workers. Given the fact that the underlying practices only reflect the use of non-standard employment, and not any policies related to incomes, this is not too surprising. The results confirm that workers in firms with screening strategies are more likely to have careers with high levels of employment security. This is in line with the *stepping stone* scenario, that argues that employers use non-standard employment to screen workers' quality, invest in their human capital and are more likely offer permanent contracts (employment security) if the quality is confirmed. In contrast, workers in firms with cost reduction strategies are more likely to experience careers characterized by non-employment or precarious non-standard employment. This is in line with the *trap* scenario, that considers cost reduction strategies as the main reason for firms to hire workers on non-standard contracts, resulting in repeated spells of non-standard employment or unemployment for the workers in these firms. Workers in firms with adaptability strategies are more likely to have careers characterized by long-term fixed-term employment compared to workers in firms with other strategies, but are still much more likely than workers in firms with cost reduction strategies to have careers characterized by higher levels of employment security as well. This also indicates that working in firms with adaptability strategies has less of a scarring effect than working in firms with cost reduction strategies.

Multichannel sequence analysis furthermore allowed us to look beyond simple stepping stone and trap outcomes and to diversify career outcomes in terms of both employment and income security. Our analysis reveals that 23.5% of workers with a non-standard contract follow a career trajectory that deviates from the traditional dichotomy between stepping stones and traps, making a trade-off between employment and income security. This type of analysis is able to give more nuanced image of the quality of the career trajectories than more traditional methods could have painted as it allows for investigating the long term consequences beyond first transitions or first employers in a multidimensional perspective.

A main contribution of this chapter is to show the considerable importance of employers' strategies on the outcomes of non-standard employment, an aspect that has remained underexposed in previous research despite being the key mechanism in theories on the outcomes of non-standard employment. Although contexts determine the possibilities for using non-standard employment, and individuals make employment decisions based on their own restrictions and preferences, employers also have a significant influence on whether non-standard employment functions as a stepping stone or as a trap for their workers that cannot and should not be neglected. Using non-standard employment practices as indicators of employers' strategies offers new opportunities to connect the labour demand side to the outcomes on the labour supply side on a large scale, without having to rely on limited survey samples of employers who might not have an explicit or thought-trough strategy for using non-standard employment, or whose practices deviate from their stated strategies.

The results however also show that, in our operationalisation, employer strategies are not the most important factor in determining outcomes of non-standard employment. Though they still contribute 19% of the total explained variance, individual characteristics and firm characteristics play a larger role in explaining the career outcomes of non-standard employment. This could be due to the fact that firms with particular strategies hire more workers with a particular individual characteristic, or to employers having different strategies for different roles in the firm. The importance of the share of high-paid workers in the firm in the analyses points in that direction. Future research could therefore aim to try to distinguish between various employer strategies for different types of jobs, for instance distinguishing between low, medium and high paid jobs in the firm.

Being one of the first studies to attempt to connect employers' strategies to career outcomes of workers in non-standard employment, this study does have some limitations. First, we could not include the share of temporary work agency workers in our analysis due to data limitations. This is however likely an important indicator of employers' strategies as well. Second, as the practices are based on firm-level aggregate employee statistics, we can only infer employer strategies at the firm level. It is however very likely that employers have different strategies for different types of jobs within the firm. Future research could therefore build upon this study and look into possibilities to distinguish various strategies within the firm, for instance by constructing indicators for low, medium and high-paid jobs. Third, we have only included firms with more than 50 employees in our analysis. However, smaller firms are likely to have non-standard employment strategies as well. Future research could try to investigate their strategies, for instance by looking at workforce changes over a longer period of time. Despite these limitations, we think that this study has been a fruitful first attempt to connect employers' strategies to the outcomes for their workers with non-standard contracts.

Appendices to chapter 5

Appendix 5A: Construction of firms' non-standard employment practices

To illustrate the construction of the non-standard employment practices, we use an example dataset, which is depicted in Table 5A.1. This table shows the employment status of individuals in five jobs within the same firm in the 12 months of the year. F denotes a fixed-term contract, P denotes a permanent contract, and an empty cell denotes that the job does not exist (yet or anymore) in that month. The cell in bold indicates the first record of that job in the year.

Table 5A.1: Example dataset to illustrate construction of non-standard employment practices

	Month											
ID	1	2	3	4	5	6	7	8	9	10	11	12
1	**F**	F	F	F								
2	**F**	F	F	F	F	F	P	P	P	P	P	P
3	**P**	P	P	P	P	P	P	P	P	P	P	P
4	**F**	F	F	F	F	F	F	F	F	F	F	F
5									**F**	F	F	F

F: Fixed-term. P: Permanent. **Bold**: first record within the year

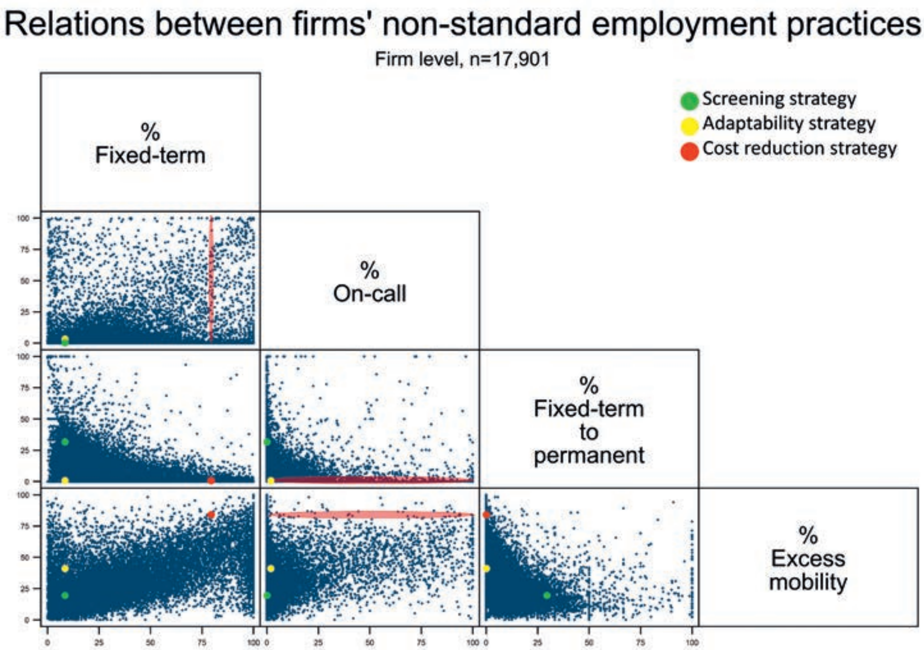
To calculate the share of fixed-term contracts within the firm, we first calculated the total job duration of all jobs within the firm. In this case, these are all non-empty cells, a total of 44 months. Second, we calculated the total job duration of fixed-term employment in the firm, which are all cells with an F, 26 in total. To come to the share of fixed-term employment in the firm, we divide the fixed-term job duration by the total job duration, so 26/44 = 59.1%. The same approach is used for the share of on-call contracts (not present in the example data).

To calculate the transition rate from fixed-term to permanent employment, we first calculated the number of jobs that were fixed-term in the first record of that job within that year (the underscored records in bold). In this example, this was the case for four jobs. Of these four jobs, one job was converted to permanent halfway through the year, namely job 2. This means that this firm has a 25% transition rate from fixed-term to permanent employment.

Finally, excess mobility is calculated in the following way. The total number of jobs in this firm is five. The total mobility is all influx and outflow of workers in the firm, minus the workers who both entered and left the firm within that same year. In this case, job 1 ended and job 5 started during the year, so total mobility is 2. The growth of the firm is 0: there were four jobs at the start of the year (5 – 1 started throughout the year), and four at the end of the year (5 – 1 ended throughout the year). So the total employee change is 0. To calculate excess mobility, we subtract the employee change from the total mobility, and divide that by the total number of jobs in the firm. In this case: (2-0)/5=0.4=40% excess mobility.

Figure 5B.1 shows the scores of the firms on the four non-standard employment practices, as well as the scores of the three non-standard employment strategies.

Figure 5A.1



Appendix 5B: Descriptive statistics

Table 5B.1: Comparison of analytical sample and total population

		Analytical Sample		Total population	
	Cluster name	N	%	N	%
1	Comfortable Careers	18,647	6.68	28,551	4.77
2	Prospects Pronto	24,700	8.85	41,210	6.88
3	Swift Security	17,534	6.29	33,285	5.56
4	Common Course	24,940	8.94	46,346	7.74
5	Moderately to Modesty	19,680	7.05	38,978	6.51
6	Precarious Permanency	27,165	9.74	45,718	7.63
7	Fortunate Fixed-term	24,729	8.86	51,785	8.64
8	Passing Permanency	4,228	1.52	10,363	1.73
9	Shift to Self-employment	12,989	4.66	32,986	5.51
10	Forever Flexible	23,282	8.35	49,851	8.32
11	Ongoing On-call	11,373	4.08	22,873	3.82
12	TWA Track	5,179	1.86	32,574	5.44
13	Troubling Temporary	8,337	2.99	17,106	2.86
14	Irregularly Inactive	2,273	0.81	9,502	1.59
15	Way to Welfare	23,799	8.53	62,782	10.48
16	Itinerary to Inactivity	19,700	7.06	47,306	7.90
17	Unfortunate Unemployed	10,419	3.73	27,860	4.65
	Total	278,974		599,076	

Table 5B.2: Descriptive statistics

Variable	Mean (sd) Individual level	Mean (sd) Firm level	Min	Max	% Individual level	% Firm level
% Fixed-term contracts	39.39 (28.17)	33.11 (27.49)	0.006	100		
% Transitions fixed-term to permanent	9.72 (11.95)	8.59 (12.78)	0	100		
% Excess mobility	34.11 (18.37)	29.64 (18.03)	0	100		
% On-call contracts	5.91 (15.41)	6.15 (15.83)	0	100		
- 0% on-call					48.40%	55.83%
- >0%-1% on-call					16.69%	10.00%
- 1%-5% on-call					10.63%	12.64%
- 5%-12.5% on-call					12.11%	8.82%
- >12.5% on-call					12.17%	12.71%
% Women in firm	56.06 (27.77)	43.46 (28.09)	0	100		
% High-paid employees	18.98 (19.76)	20.23 (20.20)	0	100		
Firm size	5012.83 (14090.71)	363.28 (1647.45)	50	116333		
- Medium firm (50-249)					28.14%	76.10%
- Large firm (250+)					71.86%	23.90%
Sector						
- Industry					7.58%	13.74%
- Construction					2.45%	5.64%
- Wholesale and retail					13.22%	18.65%
- Transport and storage					5.72%	6.09%
- Hospitality					3.91%	6.40%
- Information and communication					2.64%	3.44%
- Advising and research					5.04%	7.34%
- Portable goods					12.45%	6.16%
- Public administration					4.90%	3.16%
- Health care					27.44%	10.65%
- Culture, sports and recreation					2.23%	3.44%
- Other					12.42%	15.28%
Gender	0.58 (0.49)	n.a.	0	1		
- Male					41.59%	n.a.
- Female					58.41%	n.a.
Age	36.09 (10.85)	n.a.	18	59		
Ethnicity						
- Dutch					75.34%	n.a.
- Non-western background					14.19%	n.a.
- Western background					10.47%	n.a.
Level of education						
- Low					15.86%	n.a.
- Medium					27.10%	n.a.
- High					22.08%	n.a.
- Unknown					34.96%	n.a.
N	278,974	17,901				

Table 5B.3: Cluster characteristics of employment and income security (mean and sd)

Cluster	% time in employment	% time in permanent employment	Months until permanent employment	Within trajectory mean income	Within trajectory income standard deviation
1	95.248	59.294	22.7	5239.268	1323.598
	(10.058)	(28.277)	(-0.121)	(2407.211)	(3019.657)
2	95.326	58.262	23.49	3262.365	568.031
	(10.556)	(27.553)	(-0.095)	(511.146)	(669.276)
3	95.766	61.500	22.49	2534.812	453.194
	(10.283)	(23.424)	(0.089)	(368.672)	(405.542)
4	95.912	65.532	20.21	1954.616	380.231
	(9.409)	(18.769)	(0.059)	(420.117)	(330.971)
5	91.059	35.209	38.98	1423.664	369.725
	(14.480)	(23.416)	(0.109)	(452.672)	(307.070)
6	91.429	64.121	17.15	855.383	274.674
	(15.198)	(26.439)	(0.081)	(385.187)	(320.376)
7	89.277	7.036	55.57	2240.065	550.565
	(14.196)	(10.208)	(0.106)	(631.301)	(491.692)
8	86.069	38.120	9.84	1803.915	571.097
	(14.912)	(15.776)	(0.106)	(719.337)	(395.821)
9	92.582	4.315	51.09	2705.326	2008.312
	(11.107)	(9.100)	(0.167)	(3325.767)	(4807.750)
10	84.637	6.510	53.74	1194.864	400.889
	(16.264)	(11.368)	(0.117)	(484.604)	(299.630)
11	82.627	8.153	51.72	805.144	373.688
	(20.402)	(13.652)	(0.182)	(540.111)	(320.262)
12	78.637	4.482	58.23	1509.112	612.028
	(15.790)	(9.129)	(0.134)	(527.196)	(582.373)
13	59.140	4.840	54.86	1728.165	620.508
	(15.450)	(9.436)	(0.196	(1554.807)	(1946.588)
14	41.925	5.326	52.70	887.370	518.820
	(17.916)	(11.015)	(0.290)	(693.840)	(685.778)
15	23.160	2.899	55.93	1028.449	526.025
	(18.572)	(7.992)	(0.110)	(508.406)	(611.813)
16	28.426	4.502	52.22	1028.492	735.906
	(20.219)	(9.915)	(0.135)	(3127.769)	(4296.422)
17	23.991	3.634	52.46	1614.311	707.928
	(17.805)	(8.370)	(0.178)	(7996.389)	(2590.353)

5

Table 5B.4: Descriptive statistics of continuous variables, per cluster (mean and standard deviations, n=278,974)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	Total
Age	39.872	36.473	34.423	35.156	35.274	39.454	33.511	33.494	38.277	34.025	36.055	33.971	37.582	34.868	35.819	35.738	36.810	36.093
	(8.437)	(9.108)	(9.804)	(10.384)	(11.081)	(10.757)	(10.130)	(10.424)	(10.037)	(11.199)	(12.531)	(10.785)	(11.184)	(12.226)	(11.688)	(11.969)	(11.461)	(10.846)
% Fixed-term contracts	28.097	29.863	31.703	33.316	42.611	35.930	42.472	37.666	40.508	48.207	41.538	53.931	43.366	46.957	48.128	43.326	42.989	39.386
	(24.916)	(25.295)	(25.055)	(23.796)	(27.567)	(23.907)	(28.839)	(28.112)	(29.972)	(28.423)	(27.100)	(32.552)	(27.614)	(31.434)	(30.976)	(28.602)	(30.562)	(28.167)
% On-call contracts	1.716	2.213	3.535	4.895	5.686	6.562	4.197	6.271	6.031	6.233	23.602	5.890	4.836	12.224	6.412	7.599	6.202	5.910
	(7.577)	(7.436)	(9.631)	(10.621)	(13.664)	(13.565)	(11.906)	(15.533)	(15.810)	(15.583)	(30.836)	(16.871)	(13.172)	(23.851)	(18.023)	(18.611)	(17.166)	(15.407)
Transition rate (%)	13.037	12.664	11.705	11.195	8.407	11.616	7.977	10.957	9.109	6.949	8.303	6.338	8.076	10.070	7.798	8.834	8.556	9.719
	(12.324)	(11.552)	(10.680)	(10.430)	(9.907)	(14.471)	(10.914)	(14.001)	(12.191)	(9.954)	(11.882)	(10.579)	(10.322)	(18.173)	(12.067)	(13.419)	(11.483)	(11.951)
Excess mobility (%)	23.245	24.988	27.631	30.340	34.625	34.684	31.432	35.494	36.583	37.638	38.847	47.341	35.097	44.843	42.964	41.039	39.302	34.111
	(12.878)	(14.254)	(15.614)	(15.160)	(17.615)	(14.797)	(17.597)	(18.771)	(19.794)	(18.378)	(16.540)	(22.773)	(17.760)	(20.427)	(21.056)	(18.850)	(20.762)	(18.368)
% High-paid workers	39.907	33.123	25.228	18.777	13.820	12.200	21.577	18.322	23.137	11.515	8.956	10.922	17.536	10.452	10.577	12.904	19.588	18.978
	(21.493)	(20.034)	(18.487)	(17.472)	(16.311)	(14.408)	(19.015)	(18.619)	(22.354)	(15.389)	(11.766)	(15.440)	(18.886)	(14.250)	(14.833)	(16.918)	(21.979)	(19.757)
% Female workers	40.645	44.887	49.412	57.702	61.630	73.707	47.462	56.015	53.784	61.633	70.352	42.063	55.005	63.280	54.947	63.667	50.473	56.061
	(23.615)	(25.484)	(27.708)	(28.872)	(26.462)	(23.792)	(27.285)	(28.683)	(26.124)	(26.023)	(24.728)	(25.978)	(27.784)	(26.666)	(25.786)	(25.366)	(25.589)	(27.773)

Table 5B.5: Descriptive statistics of categorical variables, per cluster (percentages, n=278,974)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	Total
Cluster size	6.68	8.85	6.29	8.94	7.05	9.74	8.86	1.52	4.66	8.35	4.08	1.86	2.99	0.81	8.53	7.06	3.73	100
Gender																		
Male	74.98	62.22	52.78	37.47	29.65	11.99	55.97	42.34	49.83	28.46	19.25	66.89	41.47	28.95	43.37	25.15	49.94	41.59
Female	25.02	37.78	47.22	62.53	70.35	88.01	44.03	57.66	50.17	71.54	80.75	33.11	58.53	71.05	56.63	74.85	50.06	58.41
Level of education																		
Low	1.42	3.09	6.94	11.46	19.10	20.05	10.18	12.39	8.51	22.30	19.72	25.18	16.80	28.51	35.61	24.95	15.36	15.86
Medium	13.66	19.37	28.61	33.89	33.78	24.99	31.25	33.63	23.13	34.75	34.20	35.66	28.37	27.50	24.81	22.09	20.60	27.10
High	52.91	48.82	36.10	21.35	12.92	6.59	32.12	24.62	30.53	11.34	6.17	7.92	19.06	7.66	5.49	11.12	16.68	22.08
Unknown	32.02	28.72	28.35	33.30	34.20	48.37	26.45	29.35	37.83	31.61	39.90	31.24	35.77	36.34	34.09	41.84	47.37	34.96

Table 5B.5: *(continued))*

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	Total
Ethnicity																		
Dutch	84.70	83.29	82.13	81.44	78.52	79.46	80.20	79.04	78.24	76.10	77.79	63.78	66.70	67.14	60.53	63.49	46.67	75.34
Non-western	5.17	7.40	9.01	10.19	12.36	12.00	9.71	11.14	10.24	14.20	13.22	23.19	18.57	22.39	29.62	24.42	27.33	14.19
Western	10.13	9.32	8.86	8.37	9.12	8.54	10.09	9.82	11.52	9.71	8.99	13.03	14.73	10.47	9.84	12.10	25.99	10.47
% on-call contracts (categorical)																		
0	62.11	54.61	47.07	41.76	46.17	42.19	45.58	46.07	50.51	47.62	20.61	57.37	50.65	38.50	58.30	49.28	56.24	48.40
0-1	21.07	21.73	19.99	15.64	16.00	12.64	23.14	15.61	14.10	16.50	6.52	18.00	17.19	16.45	13.76	14.80	14.81	16.69
1-5	8.89	11.66	13.74	14.57	11.00	10.19	12.35	12.37	12.03	11.08	7.34	6.20	11.01	6.91	6.76	8.90	8.01	10.63
5-12.5	5.01	8.09	12.28	17.24	14.47	18.30	10.45	13.29	11.12	11.63	20.77	5.99	11.12	14.21	8.89	11.92	8.69	12.11
12.5+	2.91	3.91	6.91	10.78	12.37	16.67	8.48	12.65	12.23	13.16	44.76	12.45	10.03	23.93	12.30	15.10	12.25	12.17
Firm size (categorical)																		
50-250	29.32	30.40	30.55	28.37	26.18	17.79	35.69	34.22	31.87	29.34	26.02	35.26	31.25	25.60	23.70	25.94	30.28	28.14
250+	70.68	69.60	69.45	71.63	73.82	82.21	64.31	65.78	68.13	70.66	73.98	64.74	68.75	74.40	76.30	74.06	69.72	71.86
Sector																		
Advising and research	11.69	8.46	6.14	3.81	2.97	1.53	5.72	5.20	6.31	2.89	2.62	5.43	5.17	3.61	3.48	4.27	8.32	5.04
Construction	4.92	5.61	4.28	1.93	1.01	0.37	3.97	3.05	2.36	0.82	0.73	5.29	3.01	0.92	1.45	0.89	2.47	2.45
Culture, sports, recreation	1.52	1.30	1.50	1.48	2.41	1.68	2.65	2.48	5.54	2.92	2.85	1.91	2.75	1.67	1.74	2.60	2.64	2.23
Health care	11.96	19.84	26.73	36.13	32.24	48.59	21.86	28.29	21.09	26.60	43.04	9.19	24.83	29.56	23.82	26.57	15.77	27.44
Hospitality	0.61	1.23	1.90	2.51	5.57	2.74	4.56	5.25	3.27	7.01	6.26	4.48	4.82	5.19	4.55	5.63	5.94	3.91
Industry	13.68	11.12	9.69	5.66	9.50	4.03	8.50	5.25	3.71	7.96	1.85	8.07	6.79	2.60	10.38	3.26	7.30	7.58
Information and communication	7.82	4.89	3.12	1.40	1.21	0.68	2.90	2.67	4.93	1.14	0.92	2.28	2.40	1.50	1.98	1.85	3.32	2.64
Other services	19.37	19.59	16.19	13.58	11.14	7.21	14.05	12.58	16.61	9.60	4.87	7.59	12.99	6.64	6.59	11.22	14.10	12.42
Portable goods	3.12	4.16	6.56	8.16	10.10	14.69	8.40	12.04	12.99	14.59	12.90	33.60	12.77	27.76	22.28	21.01	18.67	12.45
Public administration	10.44	9.53	6.87	4.19	2.96	1.94	5.31	3.48	8.12	2.78	0.85	2.90	3.26	1.76	5.58	3.13	3.22	4.90
Transport and storage	3.61	3.50	4.65	7.08	4.51	6.11	8.01	5.32	6.37	5.70	5.37	7.61	6.60	3.92	6.11	6.21	5.71	5.72
Wholesale and retail	11.25	10.78	12.36	14.08	16.37	10.42	14.08	14.38	8.71	17.98	17.73	11.66	14.61	14.87	12.03	13.35	12.53	13.22

Appendix 5C: Full results

Table 5C.1: Marginal effects from the multinomial logistic regression (full results)

Cluster	Comfortable Careers	Prospects Pronto	Swift Security	Common Course	Moderately to Modesty	Precarious Permanent	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	Ongoing On-call	TWA Track	Troubling Temporary	Irregularly Inactive	Way to Welfare	Itinerary to Inactivity	Unfortunate Unemployed
Main effects non-standard employment practices																	
Share of fixed-term contracts	0.009	0.010	-0.005	-0.016	0.045***	-0.040*	0.085***	-0.010**	-0.024	0.060***	-0.035***	-0.003	0.017***	-0.007***	-0.026	-0.047***	-0.015*
	(0.008)	(0.011)	(0.009)	(0.012)	(0.006)	(0.018)	(0.012)	(0.003)	(0.014)	(0.010)	(0.008)	(0.003)	(0.002)	(0.002)	(0.021)	(0.011)	(0.006)
Share of on-call contracts (ref: 0)																	
0-1	0.636	0.724*	0.707*	0.105	0.229	-2.494**	2.904***	-0.028	-0.722**	0.828*	0.028	0.074	-0.025	0.143	-1.948***	-0.543*	-0.619**
	(0.331)	(0.327)	(0.275)	(0.331)	(0.409)	(0.878)	(0.578)	(0.080)	(0.243)	(0.408)	(0.136)	(0.158)	(0.163)	(0.078)	(0.491)	(0.248)	(0.196)
1-5	-0.771**	0.064	0.806**	1.349**	-0.056	-1.830*	1.007**	0.086	0.425*	1.272	1.085***	-0.434***	-0.058	0.050	-1.936***	-0.323	-0.735***
	(0.292)	(0.273)	(0.249)	(0.400)	(0.346)	(0.789)	(0.371)	(0.111)	(0.210)	(0.663)	(0.181)	(0.107)	(0.193)	(0.077)	(0.473)	(0.272)	(0.130)
5-12,5	-0.977**	-0.143	0.805**	1.526***	-0.078	-1.765*	0.519	0.031	0.868***	-0.731*	3.321***	-0.490***	-0.340*	0.373***	-2.429***	-0.468	-0.022
	(0.298)	(0.323)	(0.257)	(0.360)	(0.353)	(0.839)	(0.422)	(0.103)	(0.238)	(0.332)	(0.343)	(0.112)	(0.158)	(0.080)	(0.586)	(0.275)	(0.207)
12,5+	-1.752***	-2.165***	-0.230	0.391	-1.487***	-1.089	-1.141**	0.133	1.447***	-1.787***	9.704***	0.107	-0.918***	0.808***	-2.184***	-0.074	0.238
	(0.382)	(0.367)	(0.312)	(0.418)	(0.352)	(0.940)	(0.425)	(0.115)	(0.283)	(0.416)	(1.185)	(0.154)	(0.181)	(0.099)	(0.397)	(0.263)	(0.148)
Excess mobility	-0.023*	-0.058***	-0.060***	-0.087***	-0.053***	-0.006	-0.074***	0.012**	0.083***	-0.053***	-0.002	0.034***	-0.003	0.014***	0.133***	0.093***	0.052***
	(0.011)	(0.015)	(0.009)	(0.011)	(0.012)	(0.019)	(0.012)	(0.004)	(0.017)	(0.010)	(0.009)	(0.006)	(0.004)	(0.002)	(0.016)	(0.018)	(0.004)
Transition rate	0.038***	0.089***	0.068***	0.116***	0.021	0.113***	-0.017	0.018***	-0.054	-0.118**	-0.068**	-0.006	-0.008	-0.007	-0.105**	-0.077**	-0.001
	(0.010)	(0.014)	(0.010)	(0.015)	(0.022)	(0.024)	(0.041)	(0.004)	(0.028)	(0.038)	(0.022)	(0.011)	(0.009)	(0.005)	(0.037)	(0.025)	(0.009)
Interactions between non-standard employment practices																	
Share of fixed-term contracts * Excess mobility																	
0	0.025	-0.002	-0.033*	-0.068***	0.030*	-0.067**	0.130***	-0.014***	-0.018	0.100**	-0.032*	-0.005**	0.025***	-0.005**	-0.022	-0.030***	-0.013
	(0.013)	(0.015)	(0.014)	(0.018)	(0.015)	(0.022)	(0.018)	(0.002)	(0.012)	(0.036)	(0.014)	(0.002)	(0.005)	(0.002)	(0.020)	(0.008)	(0.009)
20	0.012	0.008	-0.012	-0.033*	0.040***	-0.053**	0.105***	-0.012***	-0.024	0.081***	-0.034**	-0.006**	0.021***	-0.007***	-0.029	-0.042***	-0.015
	(0.009)	(0.012)	(0.010)	(0.014)	(0.009)	(0.019)	(0.013)	(0.003)	(0.015)	(0.022)	(0.010)	(0.002)	(0.004)	(0.002)	(0.022)	(0.010)	(0.008)
30	0.006	0.013	-0.003	-0.018	0.044***	-0.045*	0.092***	-0.011**	-0.027	0.072***	-0.035***	-0.005*	0.019***	-0.007***	-0.031	-0.047***	-0.015*
	(0.007)	(0.012)	(0.009)	(0.013)	(0.007)	(0.018)	(0.012)	(0.003)	(0.016)	(0.016)	(0.009)	(0.002)	(0.003)	(0.002)	(0.023)	(0.011)	(0.007)
40	0.001	0.017	0.005	-0.005	0.046***	-0.035	0.079***	-0.008*	-0.029	0.062***	-0.036***	-0.004	0.017***	-0.008***	-0.033	-0.052***	-0.015*
	(0.007)	(0.011)	(0.008)	(0.011)	(0.006)	(0.019)	(0.011)	(0.004)	(0.016)	(0.010)	(0.008)	(0.003)	(0.003)	(0.002)	(0.023)	(0.012)	(0.006)

Table 5C.1: *(continued))*

Cluster	Comfortable Careers	Prospects Pronto	Swift Security	Common Course	Moderately to Modesty	Precarious Permanent	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	Ongoing On-call	TWA Track	Troubling Temporary	Irregularly Inactive	Way to Welfare	Itinerary to Inactivity	Unfortunate Unemployed
60	-0.008	0.021*	0.015*	0.013	0.047***	-0.014	0.054***	-0.002	-0.029	0.043***	-0.037***	0.000	0.011***	-0.009**	-0.032	-0.061***	-0.013**
	(0.008)	(0.011)	(0.006)	(0.009)	(0.005)	(0.020)	(0.010)	(0.004)	(0.017)	(0.006)	(0.009)	(0.005)	(0.003)	(0.003)	(0.023)	(0.015)	(0.004)
80	-0.015	0.021*	0.018**	0.022**	0.042***	0.006	0.032**	0.005	-0.024	0.024*	-0.036**	0.009	0.005	-0.009	-0.027	-0.066**	-0.009
	(0.010)	(0.010)	(0.006)	(0.007)	(0.007)	(0.021)	(0.010)	(0.004)	(0.017)	(0.012)	(0.013)	(0.007)	(0.004)	(0.006)	(0.025)	(0.020)	(0.008)
Share of fixed-term contracts * Transition rate																	
0	0.002	-0.007	-0.023**	-0.052***	0.031***	-0.045**	0.069***	-0.009***	-0.005	0.079***	-0.018*	-0.001	0.016***	-0.001	0.002	-0.023***	-0.013**
	(0.006)	(0.008)	(0.007)	(0.011)	(0.006)	(0.014)	(0.009)	(0.002)	(0.006)	(0.014)	(0.007)	(0.002)	(0.002)	(0.002)	(0.012)	(0.006)	(0.005)
5	0.005	0.000	-0.015*	-0.036**	0.042***	-0.043**	0.083***	-0.009***	-0.015	0.067***	-0.027***	-0.002	0.017***	-0.004*	-0.015	-0.035***	-0.013*
	(0.006)	(0.009)	(0.008)	(0.011)	(0.006)	(0.015)	(0.009)	(0.003)	(0.010)	(0.011)	(0.007)	(0.003)	(0.002)	(0.002)	(0.017)	(0.008)	(0.005)
10	0.007	0.007	-0.006	-0.019	0.051***	-0.041*	0.097***	-0.009**	-0.023	0.055***	-0.036***	-0.003	0.019***	-0.006***	-0.031	-0.047***	-0.014*
	(0.007)	(0.011)	(0.009)	(0.013)	(0.007)	(0.017)	(0.016)	(0.003)	(0.013)	(0.009)	(0.008)	(0.003)	(0.003)	(0.002)	(0.021)	(0.011)	(0.006)
15	0.010	0.014	0.002	0.000	0.059***	-0.040	0.108***	-0.010**	-0.032	0.043***	-0.044***	-0.004	0.019***	-0.008***	-0.046	-0.058***	-0.016*
	(0.008)	(0.014)	(0.011)	(0.015)	(0.009)	(0.021)	(0.025)	(0.004)	(0.017)	(0.010)	(0.008)	(0.004)	(0.004)	(0.002)	(0.025)	(0.014)	(0.008)
20	0.013	0.022	0.012	0.021	0.066***	-0.041	0.118**	-0.011*	-0.039*	0.032**	-0.051***	-0.006	0.019***	-0.010***	-0.059*	-0.068***	-0.017
	(0.010)	(0.018)	(0.014)	(0.019)	(0.012)	(0.025)	(0.034)	(0.004)	(0.019)	(0.011)	(0.008)	(0.005)	(0.005)	(0.002)	(0.029)	(0.016)	(0.009)
25	0.015	0.029	0.021	0.042	0.072***	-0.042	0.126**	-0.012*	-0.046*	0.021	-0.056***	-0.008	0.019***	-0.012***	-0.072*	-0.078***	-0.020
	(0.011)	(0.022)	(0.017)	(0.024)	(0.015)	(0.030)	(0.044)	(0.005)	(0.021)	(0.012)	(0.008)	(0.006)	(0.005)	(0.002)	(0.031)	(0.018)	(0.010)
30	0.017	0.036	0.030	0.064*	0.076***	-0.046	0.133*	-0.013*	-0.052*	0.011	-0.061***	-0.009	0.018**	-0.014***	-0.082*	-0.086***	-0.022
	(0.012)	(0.026)	(0.020)	(0.029)	(0.017)	(0.036)	(0.054)	(0.006)	(0.023)	(0.013)	(0.008)	(0.006)	(0.006)	(0.002)	(0.033)	(0.020)	(0.012)
Share of fixed-term contracts * Share of on-call contracts																	
0-1	0.009	-0.004	-0.011	0.000	0.045***	-0.045*	0.077***	-0.009**	-0.025	0.064**	-0.010**	0.001	0.014***	-0.004*	-0.033	-0.052***	-0.016*
	(0.009)	(0.014)	(0.010)	(0.013)	(0.008)	(0.022)	(0.014)	(0.003)	(0.016)	(0.021)	(0.003)	(0.003)	(0.004)	(0.001)	(0.027)	(0.013)	(0.008)
1-5	0.004	0.072**	0.037*	-0.016	0.068***	-0.107**	0.162***	-0.009	-0.039*	0.057**	-0.035***	-0.007	0.015**	-0.015***	-0.071**	-0.093***	-0.021**
	(0.011)	(0.023)	(0.015)	(0.024)	(0.017)	(0.033)	(0.022)	(0.005)	(0.018)	(0.018)	(0.006)	(0.006)	(0.005)	(0.004)	(0.023)	(0.018)	(0.007)
5-12,5	0.005	-0.013	-0.018	-0.024	0.039**	-0.042	0.062**	-0.014*	-0.016	0.097***	-0.032**	-0.008	0.041***	-0.003	-0.046	-0.017	-0.014
	(0.013)	(0.017)	(0.015)	(0.024)	(0.012)	(0.022)	(0.020)	(0.006)	(0.014)	(0.022)	(0.011)	(0.005)	(0.009)	(0.003)	(0.029)	(0.011)	(0.007)

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Table 5C.1: *(continued))*

Cluster	Comfortable Careers	Prospects Pronto	Swift Security	Common Course	Moderately to Modesty	Precarious Permanent	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	Ongoing On-call	TWA Track	Troubling Temporary	Irregularly Inactive	Way to Welfare	Itinerary to Inactivity	Unfortunate Unemployed
12,5+	0.032*	-0.010	-0.026	-0.040	0.048***	-0.032	0.060***	-0.017**	0.013	0.069***	-0.083***	-0.007	0.016**	-0.008	0.024	-0.024	-0.015
	(0.014)	(0.016)	(0.014)	(0.021)	(0.013)	(0.021)	(0.016)	(0.005)	(0.013)	(0.011)	(0.022)	(0.004)	(0.006)	(0.005)	(0.022)	(0.015)	(0.009)
Excess mobility * Share of on-call contracts																	
0-1	-0.024	-0.040*	-0.049***	-0.093***	-0.074***	-0.034	-0.065***	0.013**	0.085***	-0.066**	0.025***	0.032***	-0.006	0.012***	0.134***	0.100***	0.048***
	(0.013)	(0.018)	(0.012)	(0.013)	(0.020)	(0.026)	(0.014)	(0.004)	(0.019)	(0.023)	(0.004)	(0.007)	(0.006)	(0.002)	(0.018)	(0.021)	(0.004)
1-5	-0.047*	-0.125***	-0.113***	-0.096**	-0.094***	0.110*	-0.183***	0.017*	0.090***	-0.069*	0.046***	0.059***	-0.006	0.031***	0.184***	0.138***	0.059***
	(0.020)	(0.033)	(0.023)	(0.028)	(0.024)	(0.044)	(0.034)	(0.007)	(0.022)	(0.030)	(0.010)	(0.008)	(0.008)	(0.005)	(0.025)	(0.024)	(0.008)
5-12,5	-0.039	-0.072**	-0.041	-0.098**	-0.036*	0.047	-0.070**	0.015	0.082**	-0.090**	-0.003	0.030***	-0.032*	0.006	0.183***	0.073***	0.044***
	(0.023)	(0.025)	(0.023)	(0.031)	(0.016)	(0.028)	(0.025)	(0.009)	(0.026)	(0.027)	(0.015)	(0.006)	(0.015)	(0.004)	(0.031)	(0.017)	(0.010)
12,5+	0.027	-0.058*	-0.075***	-0.069*	-0.026	-0.009	-0.034	0.006	0.064***	-0.046**	-0.042	0.011	0.013	0.010	0.086***	0.067*	0.074***
	(0.024)	(0.024)	(0.021)	(0.027)	(0.019)	(0.031)	(0.025)	(0.008)	(0.017)	(0.017)	(0.024)	(0.010)	(0.009)	(0.006)	(0.023)	(0.027)	(0.014)
Individual characteristics																	
Gender	-7.516***	-6.156***	-2.238***	1.065***	3.039***	7.993***	-3.636***	-1.431***	-0.070	4.013***	2.326***	-0.794***	0.303***	0.331	3.052***	-0.421***	0.141
	(0.193)	(0.239)	(0.175)	(0.196)	(0.193)	(0.215)	(0.226)	(0.111)	(0.061)	(0.224)	(0.116)	(0.090)	(0.042)	(0.169)	(0.219)	(0.093)	(0.100)
Background																	
Non-western background	-3.241***	-2.979***	-1.677***	-1.852***	-1.059***	-1.355***	-2.295***	-0.688***	-0.260***	-0.549*	0.121	0.336**	0.247***	5.103***	4.058***	4.134***	1.957***
	(0.193)	(0.255)	(0.216)	(0.296)	(0.199)	(0.317)	(0.254)	(0.139)	(0.071)	(0.216)	(0.187)	(0.102)	(0.060)	(0.428)	(0.277)	(0.177)	(0.158)
Western background	-1.096***	-1.631***	-1.028***	-1.801***	-0.996***	-1.328***	-0.391	-0.115	-0.121	-0.624**	-0.185	0.377***	0.031	0.683**	1.574***	4.773***	1.878***
	(0.169)	(0.198)	(0.176)	(0.210)	(0.185)	(0.215)	(0.204)	(0.133)	(0.078)	(0.206)	(0.143)	(0.104)	(0.058)	(0.210)	(0.176)	(0.206)	(0.169)
Level of education (ref: medium)																	
Low	-3.101***	-4.352***	-2.821***	-2.547***	0.717**	3.595***	-2.767***	-0.712***	-0.334***	1.173***	0.177	0.161	0.366***	6.136***	3.299***	0.619***	0.391**
	(0.188)	(0.205)	(0.192)	(0.261)	(0.222)	(0.282)	(0.264)	(0.132)	(0.079)	(0.234)	(0.151)	(0.093)	(0.063)	(0.251)	(0.254)	(0.128)	(0.146)
High	9.674***	8.518***	1.797***	-3.122***	-4.039***	-5.445***	2.621***	2.094***	-0.018	-4.717***	-2.266***	-0.987***	-0.219***	-3.485***	-0.560***	0.364**	-0.211
	(0.269)	(0.289)	(0.228)	(0.245)	(0.171)	(0.220)	(0.395)	(0.183)	(0.080)	(0.203)	(0.143)	(0.077)	(0.049)	(0.211)	(0.149)	(0.114)	(0.141)
Unknown	1.425***	0.445**	-0.901***	-1.676***	-1.242***	2.231***	-2.008***	0.230*	-0.213**	-1.834***	0.359**	-0.425***	0.191***	0.094	2.367***	1.293***	-0.333**
	(0.130)	(0.169)	(0.162)	(0.201)	(0.225)	(0.204)	(0.226)	(0.107)	(0.069)	(0.206)	(0.129)	(0.072)	(0.048)	(0.167)	(0.165)	(0.126)	(0.113)

Table 5C.1: *(continued))*

Cluster	Comfortable Careers	Prospects Pronto	Swift Security	Common Course	Moderately to Modesty	Precarious Permanent	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	Ongoing On-call	TWA Track	Troubling Temporary	Irregularly Inactive	Way to Welfare	Itinerary to Inactivity	Unfortunate Unemployed
Age	0.516***	0.072***	-0.140***	-0.141***	-0.071***	0.160***	-0.243***	0.080***	-0.034***	-0.138***	-0.024***	-0.013***	-0.007***	-0.016	-0.043***	0.001	0.041***
	(0.011)	(0.013)	(0.009)	(0.009)	(0.008)	(0.014)	(0.016)	(0.005)	(0.003)	(0.009)	(0.006)	(0.003)	(0.002)	(0.009)	(0.009)	(0.004)	(0.005)
Age²	-0.025***	-0.015***	0.000	0.000	0.003***	-0.002**	0.005***	-0.004***	0.000	0.006***	0.008***	0.000	0.001***	0.005***	0.010***	0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Other firm characteristics																	
Firm size (ref: 50-250)	0.956***	-0.343	-0.602**	-1.169***	0.683*	1.897***	-1.781***	-0.529**	-0.491***	-0.362	0.442	-0.083	0.023	1.492***	-0.072	0.148	-0.209
	(0.234)	(0.233)	(0.209)	(0.290)	(0.334)	(0.431)	(0.343)	(0.155)	(0.072)	(0.386)	(0.358)	(0.088)	(0.055)	(0.261)	(0.193)	(0.107)	(0.123)
Share of women in firm	-0.012	-0.062***	-0.054***	-0.059***	0.022***	0.144***	-0.072***	0.018***	0.000	0.054***	0.018*	-0.017***	0.001	-0.022**	0.051***	-0.009**	-0.002
	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.013)	(0.010)	(0.003)	(0.002)	(0.007)	(0.007)	(0.002)	(0.001)	(0.008)	(0.005)	(0.003)	(0.003)
Share of high paid workers in firm	0.181***	0.141***	0.027***	-0.047***	-0.065***	-0.136***	0.062***	0.042***	0.001	-0.096***	-0.051***	-0.003	-0.004	-0.095***	-0.010	0.041***	0.010*
	(0.010)	(0.009)	(0.007)	(0.010)	(0.015)	(0.017)	(0.009)	(0.006)	(0.002)	(0.013)	(0.013)	(0.003)	(0.003)	(0.012)	(0.007)	(0.004)	(0.004)
Sector																	
Advising and research	2.030**	1.487**	1.409**	3.464***	-4.113***	-3.583**	0.677	1.740***	0.540**	-5.359**	1.528**	-0.192	0.201	-4.782***	2.603***	1.349***	0.999**
	(0.718)	(0.573)	(0.448)	(0.508)	(1.023)	(1.192)	(0.689)	(0.307)	(0.164)	(1.691)	(0.554)	(0.190)	(0.121)	(1.023)	(0.581)	(0.360)	(0.357)
Construction	-1.846	1.346	0.854	0.536	-4.856**	-1.385	1.654*	2.809***	0.662***	-5.071**	2.862*	1.109***	0.180	-3.816***	2.060**	0.753	2.149***
	(0.968)	(0.749)	(0.480)	(0.451)	(1.566)	(1.407)	(0.752)	(0.437)	(0.189)	(1.709)	(1.232)	(0.276)	(0.188)	(0.860)	(0.705)	(0.483)	(0.429)
Culture, sports and recreation	-2.119*	-2.929***	-0.306	1.811**	-2.546*	-0.461	2.243**	4.976***	0.438*	-2.260	2.508***	-0.312	0.203	-5.253***	2.849***	-0.048	1.206**
	(0.952)	(0.690)	(0.521)	(0.668)	(1.159)	(1.278)	(0.827)	(0.549)	(0.218)	(1.922)	(0.619)	(0.199)	(0.136)	(0.935)	(0.629)	(0.312)	(0.409)
Health care	-3.651***	1.870*	3.203***	7.199***	-3.800**	-1.848	3.029***	0.673*	0.494***	-5.748**	1.175**	-0.329	0.293**	-2.379*	0.173	-0.698**	0.343
	(0.621)	(0.876)	(0.537)	(0.585)	(1.110)	(1.160)	(0.847)	(0.270)	(0.137)	(1.791)	(0.418)	(0.186)	(0.089)	(1.136)	(0.443)	(0.241)	(0.283)
Hospitality	-2.084*	-0.063	-0.248	2.515***	-1.567	-2.540*	5.350***	1.027**	0.600**	-1.244	1.975***	-0.515**	0.157	-6.772***	1.347**	0.788**	1.276***
	(0.890)	(0.868)	(0.502)	(0.720)	(1.120)	(1.101)	(0.857)	(0.322)	(0.174)	(1.766)	(0.468)	(0.163)	(0.093)	(0.857)	(0.483)	(0.294)	(0.301)
Information and communication	1.580	0.451	0.663	1.099*	-4.359***	-2.255	0.161	3.779***	0.699**	-4.676**	2.812**	-0.143	0.076	-3.510**	2.400***	0.261	0.962**
	(0.852)	(0.590)	(0.561)	(0.538)	(1.153)	(1.549)	(0.890)	(0.504)	(0.223)	(1.720)	(0.896)	(0.242)	(0.134)	(1.159)	(0.609)	(0.395)	(0.349)

Table 5C.1: *(continued))*

Cluster	Comfortable Careers	Prospects Pronto	Swift Security	Common Course	Moderately to Modesty	Precarious Permanent	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	Ongoing On-call	TWA Track	Troubling Temporary	Irregularly Inactive	Way to Welfare	Itinerary to Inactivity	Unfortunate Unemployed
Other	-4.901***	-1.274**	0.982*	5.738***	-1.781	-0.815	0.951	1.474***	0.384**	-2.393	0.770	-0.048	0.247*	-3.182***	2.920***	0.094	0.832**
	(0.667)	(0.487)	(0.414)	(0.462)	(1.044)	(1.116)	(0.681)	(0.292)	(0.126)	(1.647)	(0.522)	(0.184)	(0.109)	(0.910)	(0.458)	(0.267)	(0.316)
Portable goods	-1.325	-1.206	0.773	3.616***	-5.376***	0.765	0.966	1.702***	0.395**	-3.936*	3.043***	1.227***	0.675***	-4.853***	2.385***	0.581*	0.567*
	(0.697)	(0.681)	(0.446)	(0.597)	(1.112)	(1.272)	(0.774)	(0.381)	(0.128)	(1.666)	(0.494)	(0.268)	(0.116)	(0.900)	(0.473)	(0.271)	(0.264)
Public administration	-2.216**	0.804	0.414	1.826	-4.492**	-2.514	0.400	2.581***	-0.142	-3.132	0.565	-0.037	0.256	5.087	2.306*	-1.354***	-0.353
	(0.640)	(0.765)	(0.840)	(0.992)	(1.362)	(1.445)	(1.378)	(0.599)	(0.144)	(2.216)	(0.727)	(0.253)	(0.174)	(3.374)	(1.013)	(0.203)	(0.315)
Transport and storage	-2.299**	-3.133***	-1.353*	3.395**	-5.517***	6.150	2.651	2.088***	0.220	-3.738	1.765*	-0.015	0.136	-4.614***	3.741**	-0.110	0.633*
	(0.681)	(0.611)	(0.605)	(0.995)	(1.291)	(3.317)	(1.388)	(0.502)	(0.126)	(1.997)	(0.739)	(0.165)	(0.088)	(0.820)	(1.261)	(0.232)	(0.276)
Wholesale and retail	1.396*	0.734	0.736	4.285***	-2.790*	-3.157**	1.481*	0.756**	0.475***	-3.082	2.432**	-0.186	0.315**	-5.435***	0.812	0.208	1.019***
	(0.544)	(0.474)	(0.375)	(0.454)	(1.092)	(1.111)	(0.727)	(0.236)	(0.112)	(1.822)	(0.702)	(0.151)	(0.095)	(0.856)	(0.435)	(0.245)	(0.252)

Table 5C.2: Predicted probabilities per employer strategy

	Comfortable Careers	Prospects Pronto	Swift Security	Common Course	Moderately to Modesty	Precarious Permanent	Fortunate Fixed-term	Passing Permanency	Shift to Self-employment	Forever Flexible	Ongoing On-call	TWA Track	Troubling Temporary	Irregularly Inactive	Way to Welfare	Itinerary to Inactivity	Unfortunate Unemployed
Screening	0.074[bc]	0.106[bc]	0.077[c]	0.112[c]	0.064	0.157[bc]	0.053[b]	0.020	0.039[bc]	0.057[c]	0.015[bc]	0.013[bc]	0.024	0.006[c]	0.081[c]	0.068[c]	0.036[c]
	(0.004)	(0.007)	(0.006)	(0.010)	(0.005)	(0.017)	(0.005)	(0.001)	(0.009)	(0.004)	(0.001)	(0.002)	(0.002)	(0.001)	(0.020)	(0.010)	(0.007)
Adaptability	0.055[ac]	0.078[ac]	0.067[c]	0.099[c]	0.066	0.098[ac]	0.093[ac]	0.019	0.060[ac]	0.076	0.038[a]	0.018[ac]	0.023	0.006[c]	0.091[c]	0.074[c]	0.040[c]
	(0.007)	(0.008)	(0.008)	(0.012)	(0.005)	(0.011)	(0.009)	(0.003)	(0.014)	(0.009)	(0.004)	(0.003)	(0.002)	(0.001)	(0.022)	(0.011)	(0.007)
Cost reduction	0.032[ab]	0.048[ab]	0.032[ab]	0.042[ab]	0.058	0.072[ab]	0.064[b]	0.018	0.106[ab]	0.077[a]	0.036[a]	0.039[ab]	0.028	0.015[ab]	0.167[ab]	0.107[ab]	0.059[ab]
	(0.007)	(0.008)	(0.004)	(0.006)	(0.006)	(0.009)	(0.006)	(0.002)	(0.022)	(0.008)	(0.003)	(0.004)	(0.004)	(0.001)	(0.016)	(0.017)	(0.005)

[a] Significantly different from screening strategy. [b] Significantly different from adaptability strategy. [c] Significantly different from cost reduction strategy.

Table 5C.3: Model fits of various models with different combinations of variable sets

	Model	Individual characteristics	Non-standard employment practices	Firm characteristics	FT*TR	FT*OC	FT*EX	TR*OC	TR*EX	OC*EX	ll(model)	df	McFadden R^2	BIC	BIC reduction compared to empty model	BIC difference compared to model 123	BIC difference compared to model 13	Separate variable contribution in explaining variance of model 123	Separate variable contribution in explaining variance caused by non-standard employment practices
Variable sets	model_0										-752097.6	16		1504396					
	model_1	x									-688705.2	144	0.084	1379216	-8.32%				
	model_2		x								-721945.5	128	0.040	1445496	-3.92%				
	model_3			x							-702092.5	240	0.066	1407194	-6.46%				
	model_12	x	x								-669795.5	256	0.109	1342801	-10.74%	-1.81%		14.42%	
	model_13	x		x							-664808.6	368	0.116	1334232	-11.31%	-1.24%		9.88%	
	model_23		x	x							-690949	352	0.081	1386312	-7.85%	-4.70%		37.46%	
	model_123	**x**	**x**	**x**							-654775.6	480	0.129	1315570	-12.55%				
Non-standard employment practices	model_12a3	x	FT	x							-662460.0	384	0.119	1329735	-11.61%	-0.94%	-0.34%		
	model_12b3	x	TR	x							-663202.8	384	0.118	1331221	-11.51%	-1.04%	-0.23%		
	model_12c3	x	EX	x							-661622.7	384	0.120	1328060	-11.72%	-0.83%	-0.46%		
	model_12d3	x	OC	x							-660313.9	432	0.122	1326045	-11.86%	-0.70%	-0.61%		
	model_12bcd3	x	-FT	x							-655891.9	464	0.128	1317602	-12.42%	-0.14%	-1.25%	1.08%	10.89%
	model_12acd3	x	-TR	x							-655420.5	464	0.129	1316659	-12.48%	-0.07%	-1.32%	0.58%	5.84%
	model_12abd3	x	-EX	x							-657503.2	464	0.126	1320824	-12.20%	-0.35%	-1.00%	2.78%	28.15%
	model_12abc3	x	-OC	x							-658798.3	416	0.124	1322813	-12.07%	-0.48%	-0.86%	3.84%	38.81%

Table 5C.3: *(continued)*

	Model	Individual characteristics	Non-standard employment practices	Firm characteristics	FT*TR	FT*OC	FT*EX	TR*OC	TR*EX	OC*EX	ll(model)	df	McFadden R^2	BIC	BIC reduction compared to empty model	BIC difference compared to model 123	BIC difference compared to model 13	Separate variable contribution in explaining variance of model 123	Separate variable contribution in explaining variance caused by non-standard employment practices
Interactions	model_12ia3	x	x	x	x						-654202.9	496	0.130	1314625	-12.61%	-0.0718%			
	model_12ib3	x	x	x		x					-654291.4	544	0.130	1315404	-12.56%	-0.0126%			
	model_12ic3	x	x	x			x				-654492.3	496	0.130	1315204	-12.58%	-0.0278%			
	model_12id3	x	x	x				x			-654186.3	544	0.130	1315194	-12.58%	-0.0286%			
	model_12ie3	x	x	x					x		-654679.5	496	0.130	1315578	-12.55%	0.0006%			
	model_12if3	x	x	x						x	-654366.7	544	0.130	1315555	-12.55%	-0.0011%			
	model_12iad3	x	x	x	x			x			-653840	560	0.131	1314702	-12.61%	-0.0660%			
	model_12iab3	x	x	x	x	x					-653774.8	560	0.131	1314571	-12.62%	-0.0759%			
	model_12iac3	x	x	x	x		x				-653970.8	512	0.130	1314362	-12.63%	-0.0918%			
	model_12iabc3	x	x	x	x	x	x				-653561.2	576	0.131	1314345	-12.63%	-0.0931%			
	model_12iaf3	x	x	x	x					x	-653765.1	560	0.131	1314552	-12.62%	-0.0774%			
	model_12iacf3	x	x	x	x		x			x	-653551.9	576	0.131	1314326	-12.63%	-0.0946%			
	model_12iabcf3	x	x	x	x	x	x			x	-652948.4	640	0.132	1313922	-12.66%	-0.1253%			
	m_12i_abcdef3	x	x	x	x	x	x	x	x	x	-652688.3	720	0.132	1314404	-12.63%	-0.0886%			
	m_12iabcdef3	x	x	x	All two-, three- and four-way interactions between the non-standard employment practices						-651836.4	992	0.133	1316111	-12.52	-0.0411			

Note: FT=% fixed-term; TR=% transitions fixed-term to permanent; EX=excess mobility; OC=% on-call

I

Technical Appendix I

Replication strategy

Lucille Mattijssen

During the sequence analyses done in this dissertation, I encountered two technical issues. The first issue was that I could not analyse all my sequences simultaneously due to computational limitations. The second issue was that I could not use quantitative cluster quality measures due to the large heterogeneity in my data. To solve these issues, I have developed a strategy to create robust typologies of sequences. This strategy allows for creating robust sequence typologies when using large-scale (heterogeneous) datasets. As the core of this strategy is to replicate analyses across subsamples, I call this strategy a replication strategy. In this section, I will describe the exact procedure of this replication strategy in further detail. I hope this section might be helpful for other researchers who also want to do sequence analysis on large datasets. This replication strategy can be used for both single-channel as well as multichannel sequence analysis. In this strategy, I run the sequence analyses in R (R Core Team, 2019) and use the TraMineR (Gabadinho, Ritschard, Mueller, et al., 2011) and WeightedCluster packages (Studer, 2013). For the creation of sequence tree plots with WeightedCluster, Graphviz software is required (Ellson et al., 2004). In this section, I assume that readers have a basic understanding of sequence analysis. If not, I recommend reading Cornwell (2015) and the TraMineR and WeightedCluster user manuals.

Table TA1.1: Sequence analysis replication strategy

Step	Procedure
1	**Determining the optimal number of clusters (*k*) for the typology** 1. Divide data into random subsamples that can be analysed 2. Run sequence analyses for subsamples: a. Compute a distance matrix b. Do cluster analysis for a range of cluster solutions 3. Determine the optimal number of clusters per subsample: - Qualitatively, using sequence plots, by assessing whether an additional cluster adds substantive new information to the typology - Or when using less heterogeneous data, quantitative cluster quality measures can be used as well 4. Compare optimal number of clusters across the subsamples 5. Define the most common optimal number of clusters across the subsamples, this is the final optimal number of clusters, *k*.
2	**Finding the *k* most representative clusters for the typology** 1. Re-run sequence analyses for subsamples with *k* clusters (or take the *k*-cluster solutions that were already calculated for each subsample in step 1.2.b) 2. Give substantive interpretations to the clusters that occur in the *k*-cluster solutions by using s equence plots 3. Count how often substantively similar clusters occur across all *k*-cluster solutions 4. Define the final, most representative clusters of the typology by taking the *k* most frequent occurring clusters
3	**Assigning all sequences to the *k* clusters of the typology** 1. Extract medoid sequences from the *k* final clusters 2. Compute distances between individual sequences and the medoids of the final clusters 3. Determine cluster membership by assigning individual sequences to the cluster of the closest medoid

Step 1: Determining the optimal number of clusters for the typology

The first step of the replication strategy aims to determine how many clusters the final typology should have (*k*). To do so, the large dataset first needs to be divided into random subsamples for which TraMineR is able to compute a pairwise distance matrix (1.1). In my situation, these subsamples had a size of around 43,000 individuals, but subsample sizes might depend on the available computing power. Subsequently, for each of these subsamples, a sequence analysis needs to be performed: a distance matrix is computed and, using this distance matrix, sequences are clustered (1.2). To assess which number of clusters the final typology should have, one should compare several cluster solutions for each subsample (1.2.b). It is up to the researcher to decide which maximum number of clusters they choose to calculate, though I would recommend to not be too conservative in this estimate.

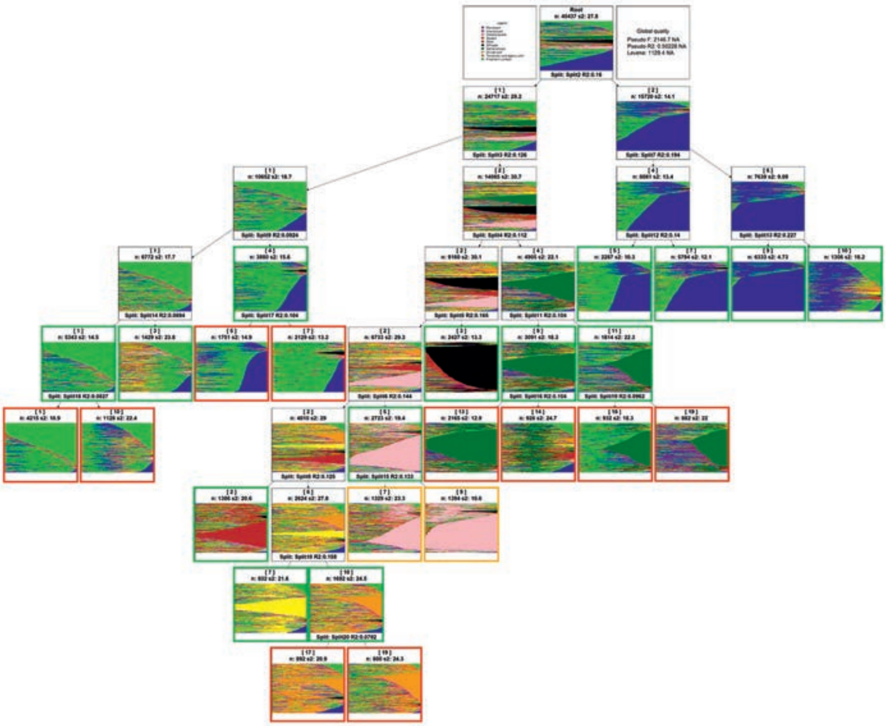
In comparing the various cluster solutions, my approach was to investigate the sequence plots of the various cluster solutions to assess qualitatively whether adding one additional cluster would add sufficient substantive new information to the typology (1.3). The moment an additional cluster no longer added substantive new information to the typology, I had reached the optimal number of clusters for the typology of that subsample. To illustrate this, I would consider a split resulting in a cluster consisting of careers characterized by on-call work and a cluster consisting of temporary work agency employment to be substantive new information, while I would consider a split resulting in a cluster with incomes of €2000 and a cluster with incomes of €1750, with similar labour market positions, to not add sufficient substantive new information. I determined whether an additional cluster added substantive new information in a qualitative fashion, as standard cluster quality measures could not be used due to the large heterogeneity in the data. Others who might have data that are less heterogeneous could rely on quantitative cluster quality measures to determine the optimal number of clusters for the typology of that subsample. Several measures are available in the WeightedCluster package. If this is not the case, it is up to the researchers themselves to determine and specify what they consider to be substantive new information. I provide an example of how I would approach this step in box TA1.1.

This procedure is then repeated for each subsample, resulting in a set of optimal numbers of clusters for the typology. The next step is to compare the optimal number of clusters across the subsamples (1.4). It is likely that the optimal number of clusters is not the same for each subsample. I choose to pick the most frequent occurring optimal number of clusters as the optimal number of clusters for the overall typology (*k*) (1.5). However, as can be seen in sections II.III to II.V of Technical Appendix II, this number is not set in stone: if there are substantive reasons to deviate from this optimal number of clusters, this can certainly be done. Researchers might also choose another way to determine the final optimal number of clusters, for instance choosing the lowest occurring or highest occurring number of clusters across subsamples. It is up to researchers to make this decision and to be transparent about their considerations.

Box TA1.1: Comparing hierarchical cluster solutions

Because I used a hierarchical clustering (Ward) in my dissertation, I could compare various cluster solutions (step 1.3) by making sequence tree plots with WeightedCluster (seqtree and seqtreedisplay) and Graphviz. Sequence tree plots combine traditional cluster dendograms with sequence plots, allowing to see very easily which new clusters emerge from splitting an existing cluster. Tree plots make it very easy to compare various cluster solutions. For those who choose hierarchical clustering methods, I can recommend using these tree plots to compare the various cluster solutions. Tree plots can also be used for multichannel sequence analysis by making one tree plot per channel using the same clustering.

The plot shows an example sequence tree plot of a single-channel sequence analysis of labour market position sequences with up to 20 clusters. In this example case, I could for instance consider 14 clusters (highlighted in green) to be the optimal cluster solution, as split 15 (highlighted in orange) in my opinion does not add much substantive new information to the typology. This also means that the other clusters that emerge from later splits (highlighted in red) are not included in the typology either.



Step 2: Finding the k most representative clusters for the typology

The aim of the second step of the replication strategy is to find the *k* most representative clusters of the typology. This is done by comparing the *k*-cluster solutions of the subsamples (2.1). In my case in chapter 2, the optimal number of clusters, *k*, was 17, so I took the 17-cluster solutions of all subsamples. For these cluster solutions, one evaluates per subsample which types of clusters can be found in the *k*-cluster typologies. This is again a qualitative procedure in which substantive interpretations are given to the clusters (2.2). This way, it is possible to identify which clusters are found in multiple subsamples, and which clusters are more unique to the subsamples. The easiest way to do so is by looking at sequence plots of the clusters.

If all clusters from all subsamples have been given a substantive interpretation or label, one can count how often the substantive clusters can be found in the subsamples (2.3). The more often a cluster is found in the subsamples, the more stable that cluster is. Sorting all occurring clusters from most frequently to least frequently occurring, the final typology would consist of the *k* most stable clusters up to the previously determined optimal number of clusters (2.4). It is possible that, around the cut-off point of the optimal number of clusters, several clusters are found equally often in the subsamples. For example, clusters 16, 17 and 18 are all found in 50% of the subsamples, while the optimal number of clusters is 17. In that case, it is up to the researcher to decide where to place the cut-off point.

Step 3: Assigning all sequences to the clusters of the typology

As the typology is finalized substantively, the final step is to assign all individuals from all subsamples to the *k* clusters of the final typology. This can be done by clustering sequences around the medoid sequences of the clusters of the typology. These medoids can be retrieved from the subsamples that contain these clusters in the cluster solution corresponding to the optimal number of clusters (3.1) using the *disscenter* function in TraMineR. It can be recommended to retrieve the medoids from the subsample that contains most of the clusters from the final typology, given that the existence of clusters is also dependent on the existence of the other clusters, and so the medoids are also related to the other medoids. It is possible that one subsample contains all clusters from the final typology, but that is not necessarily the case. If there is no subsample that contains all clusters from the final typology, the medoids from the remaining clusters can be retrieved from other subsamples. I recommend keeping the number of subsamples from which medoids are retrieved as low as possible.

Sequences can be clustered around the medoids of the representative clusters easily by computing distances between the *n* individual sequences and the *k* medoids sequences (3.2). In TraMineR, this can be done for single-channel sequence analysis with the *refseq* option in *seqdist*. Unfortunately, the *refseq* option is not available (yet) for multichannel sequence analysis, that uses *seqdistmc*. However, it is still possible to calculate the distances between the individual sequences and the k medoid sequences in multichannel sequence analysis by adding these medoids to each of the subsamples as if they were part of the original subsample, and to calculate a full *n***n* distance matrix with seqdistmc.[22] Make sure to remember which sequences are the medoids, for instance by adding them as the first or last cases in the subsamples.

The final step is to assign the individual sequences of the subsample to the cluster of the medoid sequence to which the sequence's distance is lowest (3.3). It can occur that one sequence is equally most similar to more than one medoid sequence. In that situation, one can choose to assign that sequence randomly to any of those most similar clusters, or to make some substantively justified alterations in the calculation of similarity of sequences that allow for better classification of these sequences. For instance, when I encountered this problem in chapter 5, I noticed that the problem of sequences being equally similar to more than one medoid seemed to be caused by the income sequence. Therefore, I used a different cost setting for the income sequences that allowed for better classifying these sequences based on income. Other researchers might have similar or other approaches to deal with these multi-classifiable sequences, dependent on the substantive content of their sequences.

When clustering the sequences around the medoid sequences of the final clusters of the typology, one needs to carefully check that the medoid sequence is a proper representative sequence. So though I recommend to take as many medoids as possible from one subsample, if the researcher considers that the medoid is not properly representative (and could also result in problems with classifying the original sequences), it is certainly possible to take a more representative medoid sequence from another subsample.

When a cluster of the final typology is still quite heterogeneous, it could occur that there is no single medoid sequence that can capture the full heterogeneity of the

22 This procedure is likely to be suboptimal, as it requires to calculate a n*n-distance matrix rather than a n*k-distance matrix. I have not been able to circumvent the n*n-matrix, but if others know ways to create the n*k-matrix for multichannel sequence analysis instead, I of course encourage them to use that procedure.

cluster. This for instance also was the case in the construction of the typology for chapter 5 of this dissertation. In this situation, no subsample offered a proper medoid for this heterogeneous cluster. A potential solution for this problem could be to try to capture the heterogeneity of that cluster by splitting it up further into as many clusters as necessary to represent the heterogeneity of that cluster, take the medoids from these sub-clusters, cluster the original sequences around the original set of medoids plus the new sub-cluster medoids, and later recombine the sequences that are assigned into any of the sub-clusters into one cluster again. However, if a cluster contains substantively heterogeneous sequences, researchers might consider whether it would do their typology more justice to split up the cluster and include those sub-clusters as equal clusters in the final typology. By doing so, the decisions made in the previous steps of the replication strategy might seem to have been futile, but in the end, having a typology that does justice substantively to the topic that is studied is a relevant consideration as well.

As the above procedure shows, there are many steps in which the researcher has to make decisions that likely influence the way the final typology will look like. Though some might consider this to be a downside, I think that this more qualitative approach might actually result in typologies that do better justice to the topic studied. I of course do recommend researchers that might apply this procedure to document as transparently as possible which decisions they make in the procedure and why they make them.

II

Technical Appendix II

Stability of typologies of non-standard employment trajectories through time

Lucille Mattijssen

I. Introduction

In this dissertation, I have constructed several typologies using multichannel sequence analysis. Determining the stability and robustness of typologies is not an easy thing to establish and still an ongoing debate in the field of sequence analysis. To establish the robustness of the typologies in this dissertation, I have developed a replication strategy, which was discussed in Part 1 of this Technical Appendix. Though this replication strategy is suited to determine the robustness of typologies for the same population, in itself it cannot say anything about the extent to which these typologies will also be robust over time.

In part two of this Technical Appendix, I aim to investigate the robustness of the typology of non-standard employment careers through time. For this purpose, I will compare the typology for the population of workers who entered non-standard employment in 2007, used in chapters 2 and 4 of this dissertation, to the typology for the population of workers who entered non-standard employment in 2010, used in chapter 5 of this dissertation. I will compare the cohort in two ways: first by modelling the 2010-typology to the 2007-typology, and second by creating the 2010-typology from scratch with the replication strategy.

Though the target population only differs in cohort, there might be external factors that have had an effect on the career development of workers starting in non-standard employment between 2007 and 2010, which in result might affect the typology. As there have been no significant changes in the legislation around non-standard employment in that period, the main external factor that could be responsible for differences through time is the start of the economic crisis in the end of 2008. The adverse economic conditions are likely to have negatively influenced the career development of workers in non-standard employment. For instance, the share of the workers starting in non-standard employment having a permanent contract one year later decreased from 14.8% for the 2007 cohort to 12.6% for the 2010 cohort. The share of workers having a permanent contract five years later even decreased from 35.3% to 28.4% (CBS Statline, 2021a). These developments will likely also work through in the typologies of their careers. The question is, to what extent do these development affect the typology: do we find new types of careers, or does the change remain limited to shifts in cluster sizes?

II. Creating typologies

To compare the two cohorts, I could not use the typology for the 2007 cohort that was used in chapters 2 and 4 of this dissertation: the typology of the 2007 cohort was made using sequences with a length of 96 months, while for the typology of the 2010 cohort only sequences of 72 months were available. To make the typologies comparable, I needed to re-create the typology of 2007 with the sequences limited to 72 months as well. Next to this, I constructed two typologies for the 2010 cohort: one modelled after the original 2007 typology and one from scratch. The first option would ensure comparability to the 2007-typology and allows for assessing shifts in the distribution of workers over clusters. The second option allows for seeing changes in the typology through time. The construction of the three typologies will be discussed in the next sections.

II.I. Typology for the 2007 cohort

I replicated the sequence analysis of chapter 2 for the 2007 cohort, but I limited the sequence length to 72 months instead of 96 months. The 72-month restriction also made it possible to include more individuals in our analysis of 2007 than I could when using 96-month sequences, as more individuals provided sufficient information to follow them for 72 than for 96 months. In total, 696,272 sequences could be analysed, 15,892 more than I could in chapter 2 due to the 96-month restriction.

Due to computational limitations, I could not analyse all sequences simultaneously. I therefore applied the replication strategy. I randomly split the data into 16 groups of 43,517 sequences and ran sequence analyses for these subsamples. All sequences were clustered using a Ward clustering with a Hamming distance cost setting that prevents sequences to be aligned using insertions and deletions, making it more sensitive to timing of events (Studer & Ritschard, 2016). This cost setting prevents, for instance, that sequences with quick transitions to permanent contracts and sequences with late transitions to permanent contract are labelled as similar, while it is substantively is a very big difference to make a late transition to permanent employment than to make a quick transition to permanent employment. The substitution costs were kept constant for both the employment position and the income sequence, and both channels were given equal weights in the analysis.

The results from these sequence analyses were compared qualitatively via the replication strategy suggested in Technical Appendix I to come to a final typology that would be valid for all sequences. The results of this replication strategy can be found in Table TA2.1. This replication strategy resulted in a typology of 17 clusters. Subsample 14 contained 16 of the 17 most representative clusters, all except *Fortunate Fixed-term*.

Table TA2.1: Replication strategy 2007 typology

Subsample	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	
Original optimal number of clusters	17	17	20	18	18	17	17	17	17	19	18	17	17	16	18	19	
Clusters found in 17-cluster solutions																	Count
Comfortable Careers	2110	1774	1526	2001	1717	1632	1261	2114	1882	1750	1955	2003	1616	1680	1756	1315	16
Prospects Pronto	1918	3569	1602	1320	2441	1676	3005	2723	2532	2470	2035	2108	3238	2649	2279	2629	16
Swift Security	3177	1975	2068	2648	2577	2399	2879	1539	1387	2825	2800	1944	2775	2917	2440	2283	16
Common Course	2698	1075	1641	3904	3110	3395	3472	1750	3329	1970	2797	3594	2805	2858	2265	2562	16
Shift to Self-employment	2748	2947	2884	2746	2796	2655	2670	2814	2777	2701	2792	2893	2897	2650	2808	2735	16
Way to Welfare	4090	4767	4497	2893	4577	4911	4987	4539	4602	4604	3850	4392	4939	5162	4749	3601	16
Unfortunate Unemployed	1268	1187	1372	726	1304	1341	1280	1204	1322	1022	1050	1090	954	1174	1106	1233	16
Ongoing On-call	1251	1430		1106	1097	1417	1583	1413	1449	1378	1454	954	1580	1585	1147	1163	15
Forever Flexible	3550	2074	4816	4477	4608	3781	2902	2546		2887	3622	2056		2380	3273	4153	14
Passing Permanency	2578	1826	2560	2116	2089	3575	4167	2153	4144			1820	2124	2443		1517	13
Itinerary to Inactivity	1895				1734	1615	1103		1313	1976	1852		1851	1114	1323	1364	11
Inactive Intermezzo	4204				2555	2678	3186		2776	1656	3309		2441	2688	3197	2909	11
TWA Track	2317		1605	1652	2035	2392	1542		1884			2160	1594	2121			10
Precarious Permanent	3072				2822	4104				3218	2731	5170	3647	3113		5039	9
Regular Route	3889				3153			4196	3782		2656			2241	1703		7
Moderately to Modesty		1563		2929			1514	3537		2174			1708	2743			7
Fortunate Fixed-term			2214	2008		1729	1925	2008				2441				2103	7
Temporary to permanent 1250-2000						2566				2032		2746	2213		2051	2646	6
Temporary mixed with TWA work		5269						4510		6310	5597				4600	4312	6
Delayed temporary to permanent 3000			1560	1159							1260	1149				1953	5
Mostly temporary 2000-3000	1776				3045						1856		2010	3999			5
Inactivity (one cluster)		3617	2574	3231				3716				3087					5
Temporary to permanent 1750-		3871	3821	4993			4952										4
Mostly temporary 3000	976					1651	1089	998									4

Table TA2.1: *(continued)*

Subsample	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	
Temporary to permanent 1000-			1998						2537						2828		3
Mostly temporary 2500-3000		1416							1308	2230							3
Delayed temporary to permanent 1750-2500								1757	2553								2
Mostly temporary 2000		2962								2314							2
Mostly temporary 2000-									3940				5125				2
Temporary to non-employment				3608								3910					2
Temporary to permanent 1750		2195															1
Delayed temporary to permanent 2500-															3174		1
Delayed temporary to permanent 1250-2500			4306														1
Delayed temporary to permanent 1250-2000											1901						1
Delayed temporary to permanent 1000-1750					1857												1
Mostly temporary 2000+															2818		1
Unstable temporary mixed with on-call			2473														1
Nr clusters from final typology present	15	11	11	13	15	15	15	13	13	13	13	13	14	16	12	14	
N subsample	43517	43517	43517	43517	43517	43517	43517	43517	43517	43517	43517	43517	43517	43517	43517	43517	

The medoid for *Fortunate Fixed-term* was therefore extracted from subsample 12. Subsequently, I clustered the sequences from all 16 subsamples into the cluster to which the sequence's distance to the cluster's medoid was lowest. Some sequences were equally most similar to more than one medoid sequence. This was the case for 28,912 sequences, 4.2% of all sequences. As this was largely caused by incomes, I decided to re-cluster these sequences using a cost setting for the income categories that took into account the distance between income categories. In the original clustering, an income of €1000 is equally similar to an income of €750 as to an income of €4000. In the new clustering, I changed this to make an income of €1000 more similar to an income of €750 than to an income of €4000. This way, sequences can be better assigned into their relevant clusters than with random assignment. The costs I used can be found in Table TA2.2. If after this procedure a sequence was still equally most similar to more than one medoid, the sequence was assigned randomly to one of the clusters of the medoids to which they were equally most similar. This was the case for 74 sequences.

This 17-cluster 72-month typology substantively matches the original 17-cluster 96-month typology of chapter 2. I could therefore confidently use the representative sequences of the 72-month version of the 2007-typology to model the typology of 2010 to the original typology of 2007.

II.II. Typology for the 2010 cohort, modelled after 2007

To do so, I first split the 2010 data (n=599,076) into 14 subsamples of 42,791 or 42,792 individuals. Second, I added the representative sequences of the 2007-typology to each of our 14 subsamples as if they were part of the original dataset. Subsequently, I calculated the similarity of the sequences using the Hamming distance (Hamming, 1950). Finally, the original sequences were assigned to belong to the cluster of the medoid sequence to which they were most similar according to the Hamming distance measure. Some sequences were equally most similar to more than one medoid sequence. This was the case for 25,180 individuals (4.2%). Like in the construction of the 2007 typology, I re-clustered these sequences using the cost setting for the income categories from Table TA2.2. Remaining sequences that were equally most similar to more than one medoid were randomly assigned to one of these most similar clusters. This was the case for 79 sequences.

Table TA2.2: Cost setting for income categories

Income category	*€ 0*	*€1-€250*	*€251-€500*	*€501-€750*	*€751-€1000*	*€1001-€1250*	*€1251-€1500*	*€1501-€1750*	*€1751-€2000*	*€2001-€2500*	*€2501-€3000*	*€3001-€4000*	*€4001+*
€0	0	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.9	2.1	2.5	3
€1-€250	1	0	1	1.1	1.2	1.3	1.4	1.5	1.6	1.8	2	2.4	2.9
€251-€500	1.1	1	0	1	1.1	1.2	1.3	1.4	1.5	1.7	1.9	2.3	2.8
€501-€750	1.2	1.1	1	0	1	1.1	1.2	1.3	1.4	1.6	1.8	2.2	2.7
€751-€1000	1.3	1.2	1.1	1	0	1	1.1	1.2	1.3	1.5	1.7	2.1	2.6
€1001-€1250	1.4	1.3	1.2	1.1	1	0	1	1.1	1.2	1.4	1.6	2	2.5
€1251-€1500	1.5	1.4	1.3	1.2	1.1	1	0	1	1.1	1.3	1.5	1.9	2.4
€1501-€1750	1.6	1.5	1.4	1.3	1.2	1.1	1	0	1	1.2	1.4	1.8	2.3
€1751-€2000	1.7	1.6	1.5	1.4	1.3	1.2	1.1	1	0	1.1	1.3	1.7	2.2
€2001-€2500	1.9	1.8	1.7	1.6	1.5	1.4	1.3	1.2	1.1	0	1.1	1.5	2
€2501-€3000	2.1	2	1.9	1.8	1.7	1.6	1.5	1.4	1.3	1.1	0	1.3	1.8
€3001-€4000	2.5	2.4	2.3	2.2	2.1	2	1.9	1.8	1.7	1.5	1.3	0	1.4
€4001+	3	2.9	2.8	2.7	2.6	2.5	2.4	2.3	2.2	2	1.8	1.4	0

II.III. Typology for the 2010 cohort, from scratch: part 1

[This typology was used in chapter 5 of this dissertation.]

To construct the 2010 typology from scratch, I also used the replication strategy. I first used the 14 subsamples of the 2010 cohort and ran sequence analyses for these subsamples. All sequences were clustered using a Ward clustering with a Hamming distance cost setting. The substitution costs were kept constant for both the employment position and the income sequence, and both channels were given equal weights in the analysis.

The results from these sequence analyses were compared qualitatively via the replication strategy discussed in Technical Appendix I to come to a final typology that would be valid for all sequences. First, for each subsample, I examined the hierarchical 25-cluster solution to see at what point an additional cluster did not add new information to the typology. In this decision, I attached more value to differences between clusters in terms of employment positions than in terms of income levels. In seven of the 14 subsamples, the optimal solution had 17 clusters. Second, I compared the 17-cluster solutions of the 14 subsamples to assess which clusters were most common in the 14 subsamples. 16 clusters appeared at least six times in the 14 subsamples and could therefore be seen as the most stable clusters. Subsample 3 contains all 16 most representative clusters. The results from the replication strategy can be found in Table TA2.3.

II.IV. Intermezzo: the issue of Turbulent Temporary

Though the replication strategy would result in a typology of 16 clusters, I struggled with the cluster labelled *Turbulent Temporary*. This cluster contains sequences that are all characterized by instability, but various types of instability. If one would further split up this cluster, the result would be one cluster characterized by transitions from fixed-term employment to permanent employment, and back again to fixed-term employment, with mixed incomes (similar to the cluster *Passing Permanency* that was found in subsamples 2, 10 and 12), and a cluster characterized by transitions from fixed-term employment to unemployment (and sometimes back to fixed-term employment), with mixed incomes as well. In terms of labour market outcomes, these are substantively different career paths.

The fact that two substantively different career paths are mixed into one cluster leads to a methodological issue and a substantive issue. The methodological issue comes into play in the third step of the replication strategy. In this step, I extract the medoid sequences from the most representative clusters and use those to re-cluster all sequences from all subsamples to the most representative clusters, even if these clusters are not originally found in the 17-cluster solution of that subsample. For this purpose, the medoid sequences need to be a proper representation of the clusters. For most clusters, this is the case. However, because *Turbulent Temporary* is such a diverse and unstable cluster, it is difficult to find one medoid sequence that properly represents all sequences. I have extracted several *Turbulent Temporary* medoids from different subsamples, but the medoid always resulted in a cluster that is substantively different from the original *Turbulent Temporary* cluster that resulted from the original Ward clustering.

To illustrate, I created Figure TA2.1. The left plots shows the original *Turbulent Temporary* cluster from subsample 3, the subsample that contains all most representative sequences. The two plots in the middle show the employment status and income sequences of the 16 medoid sequences of subsample 3. Sequence number 2 is the medoid of the *Turbulent Temporary* cluster. The right plot then shows what the cluster that should be *Turbulent Temporary* looks like if I re-cluster the sequences from subsample 3 around the 16 medoids of subsample 3. As you can see, the re-clustered version of *Turbulent Temporary* does not contain any sequences characterized by transitions to permanent employment and back, while they were there in the original *Turbulent Temporary* cluster. Vice versa, if the medoid sequence would be more similar to a *Passing Permanency* sequence, the result would be that all sequences with transitions from fixed-term to unemployment and back end up in different clusters where they should not have been. Though this outcome is logical in a mathematical sense, it does substantively no justice to the original typology. Clustering around medoids is thus not always suited in the case of heterogeneous clusters. However, it is the only way to cluster all sequences to the representative typology.

This methodological issue could be solved by splitting the original *Turbulent Temporary* cluster into two clusters: one similar to *Passing Permanency*, and one containing the sequences with transitions to unemployment, that could be re-labelled as *Troubling Temporary*. I could then use the medoid sequences of these clusters to re-cluster the data into 17 instead of 16 clusters, and recombine the clusters into one cluster after the re-clustering process. This way, I could do more justice to the original *Turbulent Temporary* cluster.

This however brings us to the substantive issue. As concluded before, the *Turbulent Temporary* cluster originally contains two substantively different types of career paths. A career path in which a worker makes the transition from fixed-term to permanent employment and back to fixed-term employment indicates higher levels of employment security than a career path in which the worker becomes unemployed after fixed-term employment, and has to find a new fixed-term job. In answering the main research question – to what extent do employer motives influence the employment outcomes of non-standard employment for workers? – this distinction between the two career path types is substantively relevant. It would thus substantively make sense to split up *Turbulent Temporary*.

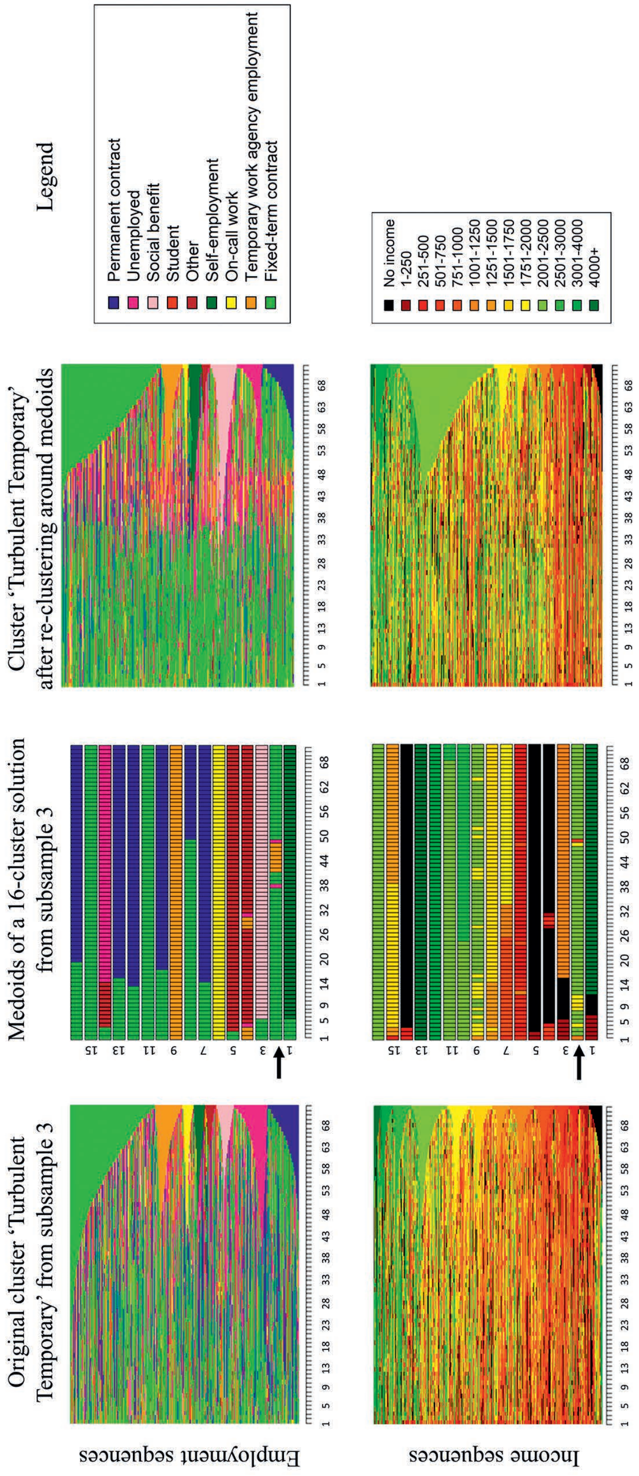
Table TA2.3: Replication strategy 2010 typology

Subsample	1	2	3	4	5	6	7	8	9	10	11	12	13	14	
Original optimal number of clusters	18	17	17	20	17	18	17	19	17	17	18	17	18	18	
Clusters found in 17-cluster solutions															Count
Comfortable Careers	1800	2289	1772	2186	2218	2145	2313	1973	1846	1729	1716	1215	1463	1261	14
Prospects Pronto	2258	2063	2500	1494	1969	2214	1891	2194	2534	2104	2514	2123	2386	2577	14
Swift Security	1989	2125	2099	1684	1856	1761	2258	1874	1339	1858	1596	1948	2044	1149	14
Common Course	1913	1155	1811	1328	1904	1993	2152	1747	2840	997	1976	2254	1513	1629	14
Ongoing On-call	926	1706	1651	1753	1151	1631	1521	1754	1480	1726	1864	1583	1170	1525	14
TWA Track	2973	4947	1846	2402	2322	3078	2392	3142	2608	3419	2482	2880	3219	2622	14
Shift to Self-employment	3024	3210	3134	3303	3091	3413	3100	2875	3226	3217	3049	3175	3112	3081	14
Unfortunate Unemployed	1800	1190	1715	1678	1618	1710	1770	1259	1579	1701	1757	1587	1653	1691	14
Way to Welfare	4862	4566	5400	4839	5110	4954	4756	4697	4895	4381	4760	4786	5351	4956	14
Itinerary to Inactivity	1550	2873	1331	1760	1547	936	1542	2457	1580	1794	1648	1893	1513	1323	14
Irregularly Inactive	3438		3072	1411	3532	1663	1680		3089	2871	1506	1425	2040	3537	12
Turbulent Temporary*	4591		4986	4058	3382	3385	4644	5405	4395		4493		3277	2856	11
Precarious Permanent		4389	4966	3788		5338		4491	3758		5078	3377		5731	9
Forever Flexible		3737	1998		4014	3331		2722	2699	6274		4191		3886	9
Moderately to Modesty			1499	3136				1527	1567		2083	2667			6
Fortunate Fixed-term			1410	1485	1181	1252	2834				1101				6
Temporary to permanent, €1000-2000	2760				3169		4255			3464			2833		5
Temporary to permanent, <€750	1257				3037		1305			1927			2998		5
Largely fixed-term, €2500+		1834								2267		3160	1757	2162	5
Largely fixed-term, €2000		1486	1602				2252			1516			1413		5
Largely fixed-term, €3000+	1361							1214	1285					1255	4
Largely fixed-term, €2000-€2500					1691	1916		1911	2071						4
Inactive intermezzo				1776		2071		1549			1040				4
Passing permanency*		1815								1547		1989			3

Table TA2.3: *(continued)*

Subsample	1	2	3	4	5	6	7	8	9	10	11	12	13	14	
Largely fixed-term, <€2500	4007										4128		5049		3
Churning fixed-term, <€1500							2126					2538			2
Temporary to permanent, €1500-€2000		1856													1
Delayed temporary to permanent, mixed incomes	2282														1
Largely fixed-term, <€3000				4710											1
Delayed inactivity and unemployment		1550													1
Delayed temporary to permanent, €2000-€2500														1550	1
Nr clusters from final typology present	12	12	16	15	14	15	13	14	15	12	15	14	12	14	
N subsample	42791	42791	42792	42791	42792	42791	42791	42791	42791	42792	42791	42791	42791	42791	

Figure TA2.1: Illustration of methodological problem with medoids of turbulent clusters



What strengthens the argumentation for splitting up *Turbulent Temporary* is the fact that a *Passing Permanency* cluster, which would be one of the two split-up clusters, is not only found in three other subsamples, but mostly that *Passing Permanency* and *Turbulent Temporary* are mutually exclusive: if *Passing Permanency* is present in a 17-cluster solution, *Turbulent Temporary* is absent, and vice versa. This shows that these clusters are related as well. Taking together these methodological and substantive considerations, I have therefore decided to split up the original *Turbulent Temporary* cluster into a *Passing Permanency cluster* and a more homogeneous *Troubling Temporary* cluster.

II.V Typology for the 2010 cohort, from scratch: part 2

As I decided to split up the original *Turbulent Temporary* cluster into a *Passing Permanent* cluster and a more homogeneous *Turbulent Temporary* cluster, I ended up with a 17-cluster typology. For these 17 clusters, I needed to find medoid sequences. As subsample 3 contained 15 of the 17 representative clusters, all except the two clusters resulting from the split up of *Troubling Temporary*, that was the first source for medoid sequences. 14 of the medoid sequences were suitable for creating a final typology. Only the sequences for *Precarious Permanent* turned out to not be suited to model all subsamples to the most representative typology. The inclusion of these sequences resulted in the misclassification of sequences: for instance, sequences that should have been classified as *Precarious Permanent* were classified as *Comfortable careers*. Therefore, I looked for a suitable medoid for *Precarious Permanent* in another subsample. A suitable medoid was found in subsample 12.

As no 17-cluster solution contained sequences for both *Passing Permanency* and *Troubling Temporary*, I looked in larger cluster solutions that do contain both clusters for the medoids. The split of *Turbulent Temporary* into two clusters was found earliest in subsample 8, where the 18-cluster solution already contained a split of *Turbulent Temporary* into *Passing Permanency* and a more homogenous *Troubling Temporary*. In subsample 3, this split only occurs from the 23-cluster solution onward. Therefore, I decided to use the medoid sequences of *Passing Permanency* and *Troubling Temporary* from the 18-cluster solution from subsample 8. These medoids completed the set of 17.[23]

23 Actually, a better medoid sequence for Passing Permanency could be found in subsample 12. This medoid was better able to prevent Passing Permanency sequences to be clustered in clusters characterized by lasting transition to permanent employment (a so-called stepping stone cluster). However, given that the existence of *Passing Permanency* was already as subjective decision, and that the *Passing Permanency* from subsample 12 resulted from a split of a stepping stone cluster and not from a *Turbulent Temporary* cluster, I decided to stick to the *Passing Permanency* medoid of subsample 8.

To re-cluster all subsamples to these medoids, the 17 representative sequences were added to all 14 subsamples as if they were part of the original data. I then calculated the similarity of all original sequences to the 17 medoid sequences and assigned the original sequences to the cluster of the medoid sequence to which the sequence was most similar. Some sequences were equally most similar to more than one medoid sequence. This was the case for 25,501 sequences (4.3%). To solve this issue, I re-clustered these sequences using the cost setting for the income categories from Table TA2.2. Remaining sequences that were equally most similar to more than one medoid were randomly assigned to one of these most similar clusters. This was the case for 280 sequences.

III. Comparison of typologies

An overview of the three typologies (2007, 2010 modelled to 2007 and 2010 from scratch) can be found in Table TA2.4. I will not substantively discuss all clusters here in detail (for that I refer to chapters 2 and 5), but focus on the main similarities and differences between the typologies.

As the first typology for 2010 was modelled to match the typology of 2007, there are no substantive differences in the types of clusters that the typology contains. The only differences between the typologies can be found in the relative sizes of the clusters. These are generally minor, though some larger differences can be found. For instance, it is interesting to see that clusters 15 to 17, which are characterized by non-employment, are larger in 2010 than in 2007. We also see that career types characterized by non-standard employment, such as 8, 9, 11, 12 and 13, have increased as well. In contrast, clusters 2 to 5, which have high levels of employment and income security, have become smaller in 2010. These shifts might indicate an effect of the economic recession that started between 2007 and 2010, decreasing non-standard workers' probabilities to have careers with high levels of employment and income security. The exception is cluster 1, which has the highest levels of employment and income security: this cluster increased between 2007 and 2010.

If we model the 2010 typology from scratch, it actually also does not differ very much from the 2007-typology. 15 of the 17 clusters were substantively the same as the clusters in the 2007 typology. Two clusters differed from the original typology. One cluster that was new in the 2010-from-scratch typology was a cluster that consisted of unstable flexible employment with unstable incomes at various income levels, which I named *Troubling Temporary*. This cluster replaces the cluster *Regular Route*, that was characterized by transitions from fixed-term to permanent employment with lower to medium incomes.

This can also be seen as an indication that non-standard employment trajectories have become less stable between 2007 and 2010. The other new cluster, *Irregularly Inactive*, is characterized by inactivity. Though it is partially similar to the original *Inactive Intermezzo* cluster, the main difference is that in these sequences, the inactivity spell is largely concentrated at the end of the sequence, rather than in the middle.

Table TA2.4: Comparison of typologies of non-standard employment trajectories

		Typology					
		2007		2010 to 2007		2010 from scratch[a]	
	Cluster name	n	%	n	%	n	%
1	Comfortable Careers	29,407	4.22	28,510	4.76	28,551	4.77
2	Prospects Pronto	54,303	7.80	41,596	6.94	41,210	6.88
3	Swift Security	47,267	6.79	34,656	5.78	33,285	5.56
4	Common Course	61,940	8.90	38,878	6.49	46,346	7.74
5	Moderately to Modesty	43,864	6.30	32,940	5.50	38,978	6.51
6	Regular Route	42,863	6.16	25,928	4.33		
7	Precarious Permanency	48,222	6.93	33,938	5.67	45,718	7.63
8	Fortunate Fixed-term	63,157	9.07	58,679	9.79	51,785	8.64
9	Shift to Self-employment	32,704	4.70	33,486	5.59	32,986	5.51
10	Passing Permanency	16,978	2.44	12,719	2.12	10,363	1.73
11	Forever Flexible	57,427	8.25	51,508	8.60	49,851	8.32
12	Ongoing On-call	21,550	3.10	24,451	4.08	22,873	3.82
13	TWA Track	27,417	3.94	32,915	5.49	32,574	5.44
14	Inactive Intermezzo	16,531	2.37	14,231	2.38		
15	Way to Welfare	59,897	8.60	58,851	9.82	62,782	10.48
16	Itinerary to Inactivity	47,446	6.81	43,744	7.30	47,306	7.90
17	Unfortunate Unemployed	25,299	3.63	32,046	5.35	27,860	4.65
18	Troubling Temporary					17,106	2.86
19	Irregularly Inactive					9,502	1.59
	Total	696,272		599,076		599,076	

[a] For the sake of the comparison of the typologies, the numbering of the clusters for the 2010 from scratch typology deviates from the numbering of the clusters in chapter 5.

The two 2010 typologies can also be compared to see to what extent individuals are assigned to the substantively same clusters in both typologies. This comparison can be found in Table TA2.5. The table shows that both typologies in most cases classify the sequences in the substantively similar clusters (76.1%). The cluster that performs least well is *Passing Permanency*. We see that several sequences that would be classified as *Passing Permanency* in the 2007 version are re-classified as *Common Course* and *Fortunate Fixed-term*. This is likely due to a difference in the medoid sequence of *Passing Permanency* between the 2007-version and the 2010 version. Next to this, we see that the new 2010 cluster *Troubling Temporary* is mix of sequences that in 2007 were classified as *Fortunate Fixed-term, Forever Flexible* or *Unfortunately Unemployed*. This also explains why the share of matching sequences is lower for these three clusters.

Individuals that would be classified in the cluster *Regular Route* in the 2007-version, are classified in 'neighbouring' clusters *Moderately to Modesty* and *Precarious Permanent*. We also see that most of the individuals classified as *Inactive Intermezzo* or *Itinerary to Inactivity* in the 2007-version of the typology are now classified in *Itinerary to Inactivity*, while only a few of both these clusters are classified in the new cluster *Irregularly Inactive*. As the new cluster focuses on sequences with a inactivity spell at the end, it will have taken those from the two original inactivity clusters, while all others are now combined in *Itinerary to Inactivity*.

IV. Conclusion

The comparison of the three typologies shows that, between 2007 and 2010, the differences between typologies are minor. When a completely new typology is created, only two substantively new clusters emerge. One of the new clusters, *Irregularly Inactive*, furthermore only differs in the timing of inactivity to the original *Inactive Intermezzo*, and will, together with *Itinerary to Inactivity*, capture practically the same types of career paths. The cluster *Troubling Temporary* does reveal a career path that had been absent in 2007, that reflects the consequences of the economic deterioration for the careers of workers. However, the existence of this cluster was the result of both methodological and substantive problems related to the replication strategy and could therefore also be disputed. At the same time, it is not impossible to assume that similar problems could just as easily have occurred in the construction of the 2007 typology, and that it was just sheer luck that this problem did not occur in the construction of the 2007 typology. After all, the replication strategy in the end is a qualitative method that cannot function without decisions made by the researcher.

This qualitative aspect also makes it more difficult to make hard recommendations for others using (multichannel) sequence analysis when comparing typologies for different cohorts. Though methods are being developed to measure to what extent cohorts differ in their sequences (Liao & Fasang, 2021), there here are no hard measures yet that express the similarity of typologies for different cohorts. Developing measures that could do this would thus be a very interesting area for future research. Up until then, my more qualitative approach could function as an example for other researchers struggling with the comparison of typologies over time.

Table TA2.5: Comparison of the 2007-version of the 2010-typology and the 2010 from scratch-typology[1]

Outcome in 2010 modelled to 2007 typology	Outcome in 2010 from scratch typology: 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	96.9%	0.9%	0.1%	0.0%	0.1%		0.5%	0.2%	0.2%	0.2%	0.0%	0.1%	0.0%		0.0%	0.0%	0.0%	0.7%	0.0%
2	0.4%	95.3%	0.8%	0.2%	0.5%		0.2%	0.7%	0.0%	0.8%	0.0%	0.0%	0.1%		0.0%	0.0%	0.0%	0.9%	0.0%
3	0.1%	0.2%	87.5%	4.4%	0.7%		2.6%	1.2%	0.0%	1.6%	0.1%	0.0%	0.7%		0.1%	0.0%	0.0%	0.7%	0.0%
4	0.1%	0.4%	1.8%	85.0%	0.5%		0.8%	6.0%	0.0%	1.0%	0.0%	0.0%	3.2%		0.5%	0.0%	0.0%	0.9%	0.0%
5	0.3%	0.5%	1.0%	9.4%	60.4%		13.0%	1.5%	0.2%	0.1%	6.9%	0.6%	0.2%		2.0%	0.1%	0.2%	3.6%	0.1%
6	0.9%	1.6%	2.7%	16.2%	32.2%		35.1%	0.0%	0.2%	3.3%	4.9%	0.3%	0.6%		1.1%	0.3%	0.3%	0.4%	0.1%
7	0.5%	0.6%	0.8%	6.8%	6.1%		72.4%	0.1%	0.4%	2.2%	1.8%	1.6%	0.3%		3.8%	0.5%	0.6%	1.3%	0.2%
8	0.1%	0.3%	0.3%	0.4%	6.2%		0.1%	69.2%	0.1%	1.2%	11.2%	0.1%	1.8%		0.4%	0.1%	0.0%	8.4%	0.0%
9	0.3%	0.1%	0.1%	0.1%	0.3%		0.8%	0.5%	95.8%	0.1%	0.5%	0.1%	0.3%		0.3%	0.1%	0.0%	0.5%	0.1%
10	0.1%	0.7%	2.4%	13.0%	0.0%		5.4%	24.9%	0.1%	42.4%	2.5%	0.2%	6.2%		0.5%	0.2%	0.1%	1.2%	0.1%
11	0.0%	0.0%	0.0%	0.2%	5.8%		3.6%	7.4%	0.3%	1.8%	69.4%	1.0%	0.2%		2.7%	0.4%	0.2%	6.8%	0.2%
12	0.0%	0.0%	0.0%	0.2%	0.8%		7.1%	0.4%	0.4%	0.4%	1.3%	85.3%	0.3%		1.4%	0.6%	0.2%	1.1%	0.5%
13	0.0%	0.0%	0.0%	0.1%	1.9%		1.1%	0.1%	0.3%	0.2%	3.4%	0.8%	84.7%		3.5%	0.4%	1.6%	0.6%	1.3%
14	0.0%	0.0%	0.0%	0.0%	0.2%		0.7%	0.2%	0.3%	0.1%	0.3%	0.2%	0.4%		3.3%	68.8%	2.3%	1.5%	21.5%
15	0.0%	0.0%	0.0%	0.0%	0.4%		1.1%	0.3%	0.1%	0.1%	1.8%	0.2%	0.4%		94.4%	0.3%	0.3%	0.4%	0.2%
16	0.0%	0.0%	0.0%	0.0%	0.1%		0.6%	0.1%	0.1%	0.1%	0.2%	0.2%	0.1%		1.1%	83.0%	0.1%	2.0%	12.2%
17	0.0%	0.1%	0.1%	0.0%	0.3%		0.9%	0.3%	0.0%	0.2%	0.6%	0.1%	1.2%		1.8%	0.4%	81.9%	11.4%	0.6%
18																			
19																			

[1]: Row percentages. Names of clusters can be found in Table TA2.4.

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Summary

Non-standard employment – employment on a fixed-term contract, on-call contract or temporary work agency contract – has become increasingly more common throughout Europe in the last two decades. Particularly in the Netherlands, the share of non-standard employment has increased significantly, from around 16% in 2003 to well over 25% from 2015 onwards (CBS Statline, 2021c). As non-standard employment is generally considered to be inferior to permanent employment due to, on average, lower wages, fewer fringe benefits and training opportunities (De Beer, 2016), a central question of research has become to what extent non-standard employment offers workers *prospects* of permanent, stable employment, or results in *precarity* of repeated unstable non-standard employment and unemployment.

Non-standard employment could offer workers prospects by functioning as a stepping stone to permanent employment: while working on non-standard contracts, workers acquire skills and experience that improve their career prospects both in terms of contract type and income (Mincer, 1974). Next to this, employers could use non-standard employment as a way to screen workers on their quality and productivity. If workers live up to the employer's standards, they will receive a permanent contract (Spence, 1973). In contrast, non-standard employment could result in precarity when workers get trapped in non-standard employment. When non-standard employment is mostly used by employers to adapt their workforce to economic fluctuations, these jobs offer workers no job security (Doeringer & Piore, 1971). Next to this, employers will have no incentive to invest in the human capital of these workers, as they are only employed for a limited period. This also harms the future employment prospects of workers, as future employers might assume that workers with a history of non-standard employment are of lower quality (Berton et al., 2011).

Many studies have tried to answer which of both scenario's holds. However, the way research up until now has tried to answer this question has had some limitations. The quality of outcomes is usually determined based on outcomes at single points in time (usually after *t* months or years), on one dimension (usually employment), with a limited definition of what is a "good" outcome (usually permanent employment), and with a limited definition of non-standard employment (usually grouping all types of non-standard employment together). As result, the conclusions have been mixed, with some researchers finding that non-standard employment offers prospects, while others state that non-standard employment results in precarity (e.g. De Lange *et al.*, 2013; Mooi-Reci and Dekker, 2015).

The aim of this dissertation is twofold. The first and central aim is to create a more nuanced image of the outcomes of non-standard employment by using a processual approach. With this approach, I can overcome the limitations of previous research as it allows me to study career trajectories as a whole, taking into account all events that happen in the career and going beyond single point-in-time measures. I can also take into account both the employment positions and the incomes earned throughout the career trajectory, which allows for defining “good” outcomes longitudinally and in terms of both employment and income security. Furthermore, I can distinguish between different types of non-standard employment, as they can have different outcomes for workers’ careers. With this more nuanced image of outcomes of non-standard employment I am subsequently able to address the second aim of this dissertation, which is to look into the factors that explain the outcomes of non-standard employment from three perspectives: the economic perspective, the sociological perspective, and the human resources perspective.

In ***chapter 2***, I focus on the first aim of this dissertation of creating a more nuanced image of non-standard employment with a processual approach. To apply the processual approach, I use multichannel sequence analysis (Gauthier et al., 2010; Pollock, 2007) on register data from Statistics Netherlands that allows for tracking the careers of all workers who entered non-standard employment in 2007 for eight years. This analysis results in a typology of non-standard employment trajectories that classifies careers in terms of employment security and income security. This typology shows that it is not a matter of non-standard employment either offering prospects or resulting in precarity, but that both outcomes exist simultaneously: around 30% of workers have a career that offers both employment and income security, and thus offers prospects, while around 40% of workers have a career that has low levels of employment and income security, and thus results in precarity.

However, and more importantly, the typology shows that there are many more outcomes than just prospects or precarity, as some careers combine high levels of employment security with low levels of income security, or vice versa, and are thus more difficult to classify. Next to this, the analysis shows that permanent employment is not a final outcome, as some workers leave permanent employment to start working in non-standard employment again, either voluntary or involuntary. Combined, almost 25% of workers have a career that deviates from the traditional image of prospects or precarity.

In ***chapter 3***, I look into economic explanations of career outcomes. Here, I assess the extent to which level of education, the specificity of the field of study and the cyclical sensitivity of the field of study, and their interplay, affect the school-to-work transitions of the 2009/2010 cohort of school-leavers in the Netherlands. In contexts such as the

Netherlands, it is expected that more specific fields of study result in better employment outcomes. However, it is still unknown to what extent this holds for each level of education, and whether specificity is also an asset if the field of study is vulnerable to economic fluctuations. The results show that school-leavers from more specific fields of study are more likely to have careers characterized by high levels of income security compared to school-leavers from more general fields of study. The effect of specificity is strongest for school-leavers at the ISCED 354-level (MBO4), which combines strong connections to employers with relatively high-level skills. Next to this, and in contrast to what I expected, the effect of specificity is stronger for school-leavers from cyclically sensitive fields of study.

In ***chapter 4***, I study a sociological explanation of career outcomes: occupations. More specifically, I look into whether the occupational skill level and the types of tasks executed in the occupation determine whether non-standard employment offers prospects or results in precarity. The skills and tasks related to an occupation namely largely determine to what extent workers are replaceable. Workers in occupations that require low skills and consist of routine tasks are expected to be more replaceable and therefore at risk of more precarious careers (Goldthorpe, 2007). To test this, I link the typology from chapter 2 to data from the Dutch Labour Force Survey that provides information on the occupations of these workers. This occupational information is subsequently linked to the O*NET database that contains information about which types of tasks are executed in these occupations. The results show that occupations that require high-level skills do not preclude precarious careers with low levels of employment and income security. Routine tasks also not necessarily result in precarity, as routine cognitive tasks can have positive effects on employment and income security while routine manual tasks reduce employment and income security.

Finally, ***chapter 5*** focuses on how employers' strategies for using non-standard employment – screening, adaptability or cost reduction – affect the career outcomes of workers who work on non-standard employment contracts. Screening strategies aim to create long-term employment relations and would therefore result in careers with prospects, while employers with adaptability or cost reduction strategies have no intention to offer long-term employment contracts, resulting in more precarious careers for workers. By defining strategies as patterns in a stream of decisions (Mintzberg, 1978), I derive which strategies employers have for using non-standard employment from their non-standard employment practices, such as the share of non-standard employment, the transition rate from fixed-term to permanent employment and excess mobility of workers in the firm. The results show that workers in firms with screening strategies have careers with higher levels of employment and income security, while workers in firms with cost reduction strategies have careers with low levels of employment and income security. Interestingly, the negative effects of working in a firm with an adaptability strategy remained limited, with career outcomes closer to those of workers in screening firms than to those of workers in cost reduction firms.

By using a processual approach in this dissertation, I have been able to show that there is more diversity in outcomes of non-standard employment that previously has been assumed. This approach thus offers opportunities to get more nuanced answers to both older and newer questions regarding non-standard employment from three different perspectives. All three perspectives provide insights in when non-standard employment offers prospects or results in precarity, or something in between. As it was beyond the scope of this dissertation to combine these three perspectives, future research could look into the interplay between these perspectives to see what matters most in explaining career outcomes of non-standard employment. Though using a processual approach can pose some additional challenges, e.g. computational issues and methodological considerations, I can highly recommend future research to adopt a similar approach.

Samenvatting

Niet-standaard werk – werk op basis van een contract voor bepaalde tijd, oproepcontract of uitzendovereenkomst, ook wel flexwerk genoemd – is de afgelopen twee decennia in heel Europa steeds gebruikelijker geworden. Met name in Nederland is het aandeel tijdelijke contracten sterk gestegen, van circa 16% in 2003 tot meer dan 25% sinds 2015 (CBS Statline, 2021c). Omdat flexwerk over het algemeen als inferieur wordt beschouwd ten opzichte van vast werk vanwege gemiddeld lagere lonen, slechtere secundaire arbeidsvoorwaarden en minder opleidingsmogelijkheden (De Beer, 2016), is een centrale vraag in onderzoek in hoeverre flexwerk werknemers uitzicht biedt op een vaste, stabiele baan, of resulteert in de precariteit van steeds nieuwe, onstabiele tijdelijke contracten en periodes van werkloosheid.

Aan de ene kant kan flexwerk werknemers vooruitzichten bieden door te functioneren als een opstap naar vast werk: door te werken op een tijdelijk contract doen werknemers vaardigheden en ervaring op die hun loopbaankansen verbeteren, zowel wat betreft contracttype als inkomen (Mincer, 1974). Daarnaast zouden werkgevers tijdelijke contracten kunnen gebruiken als een manier om werknemers te screenen op hun kwaliteit en productiviteit. Als de werknemers voldoen aan de eisen van de werkgever, krijgen ze een vast contract (Spence, 1973). Aan de andere kant kan flexwerk leiden tot onzekerheid wanneer werknemers vast komen te zitten in tijdelijk werk. Wanneer tijdelijke contracten door werkgevers vooral worden gebruikt om hun personeelsbestand aan te passen aan economische schommelingen, bieden deze banen werknemers geen werkzekerheid (Doeringer & Piore, 1971). Daarnaast zullen werkgevers geen prikkel hebben om te investeren in het menselijk kapitaal van deze werknemers, aangezien zij slechts voor een beperkte periode in dienst zijn. Dit schaadt ook de toekomstige arbeidsmarktkansen van werknemers, aangezien toekomstige werkgevers zouden kunnen aannemen dat werknemers met een voorgeschiedenis van flexwerk van mindere kwaliteit zijn (Berton et al., 2011).

Veel studies hebben geprobeerd om te achterhalen welk van deze scenario's nu klopt. Echter, het onderzoek dat tot nu toe hiernaar gedaan is, kent een aantal beperkingen. Zo wordt de kwaliteit van de resultaten meestal bepaald op basis van uitkomsten op bepaalde momenten in de tijd (meestal na t maanden of jaren), op één dimensie (meestal het contracttype), met een beperkte definitie van wat een "goede" uitkomst is (meestal een vast dienstverband), en met een beperkte definitie van flexwerk (meestal worden alle soorten flexwerk samengevoegd). Als gevolg hiervan lopen de conclusies uiteen, en vinden sommige onderzoeken dat flexwerk vooruitzichten biedt, terwijl anderen concluderen dat flexwerk resulteert in precariteit (bijv. De Lange *et al.*, 2013; Mooi-Reci and Dekker, 2015).

Het doel van dit proefschrift is tweeledig. Het eerste en centrale doel is om door middel van een procesgerichte aanpak een genuanceerder beeld te krijgen van de uitkomsten van flexwerk. Met deze aanpak kan ik de beperkingen van eerder onderzoek aanpakken, omdat het me in staat stelt loopbaantrajecten als geheel te bestuderen, rekening houdend met alle gebeurtenissen die zich in de carrière voordoen, en ik zo verder kan gaan dan het kijken naar uitkomsten op één bepaald moment. Ik kan ook rekening houden met zowel de arbeidsmarktposities als de inkomens die tijdens het gehele loopbaantraject zijn verdiend, wat het mogelijk maakt om "goede" resultaten longitudinaal te definiëren en in termen van werkzekerheid én inkomenszekerheid. Verder kan ik onderscheid maken tussen verschillende soorten flexwerk, aangezien deze verschillende gevolgen kunnen hebben voor de loopbaan van werknemers. Met dit meer genuanceerde beeld van de uitkomsten van flexwerk ben ik vervolgens in staat om het tweede doel van dit proefschrift uit te voeren, namelijk het onderzoeken van factoren die de uitkomsten van flexwerk verklaren, vanuit drie verschillende perspectieven: het economische perspectief, de sociologisch perspectief en het human resources perspectief.

In ***hoofdstuk 2*** richt ik me op het eerste doel van dit proefschrift, namelijk het creëren van een meer genuanceerd beeld van flexwerk met een procesgerichte benadering. Om de procesgerichte aanpak toe te passen, maak ik gebruik van multichannel sequentieanalyse (Gauthier et al., 2010; Pollock, 2007) op registerdata van het CBS waarmee de loopbanen van alle werknemers die in 2007 zijn begonnen in een flexbaan voor acht jaar kunnen worden gevolgd. Deze analyse resulteert in een typologie van flexibele loopbanen waarin de typen loopbanen kunnen worden ingedeeld in termen van werkzekerheid en inkomenszekerheid. Deze typologie laat zien dat het niet alleen gaat over of flexwerk ofwel vooruitzichten biedt ofwel precariteit tot gevolg heeft, maar dat beide uitkomsten tegelijkertijd bestaan: ongeveer 30% van de flexwerkers heeft een loopbaan die zowel werkgelegenheid als inkomenszekerheid biedt, en dus vooruitzichten biedt, terwijl ongeveer 40% van de flexwerkers een carrière heeft met weinig werk- en inkomenszekerheid, wat resulteert in onzekerheid.

Belangrijker is echter dat de typologie ook laat zien dat er veel meer uitkomsten zijn dan alleen vooruitzichten of precariteit, aangezien sommige carrières een hoge mate van inkomenszekerheid combineren met lage inkomenszekerheid, of juist omgekeerd. Deze carrières zijn dus moeilijker te labelen. Daarnaast blijkt uit de analyse dat een vast dienstverband geen definitieve uitkomst is, aangezien sommige werknemers hun vaste dienstverband verlaten om – vrijwillig of onvrijwillig – weer over te stappen naar flexwerk. In totaal heeft bijna 25% van de werknemers een loopbaan die afwijkt van het traditionele beeld van vooruitzicht of precariteit.

In ***hoofdstuk 3*** ga ik in op de economische verklaringen van loopbaanuitkomsten. Hier analyseer ik in hoeverre het opleidingsniveau, de specificiteit van de opleidingsrichting en de conjunctuurgevoeligheid van de opleidingsrichting, en hun wisselwerking, van invloed zijn op de school-naar-werktransities van schoolverlaters in Nederland van het cohort 2009/2010. In de Nederlandse context is namelijk de verwachting dat het volgen van een specifiekere opleiding resulteert in betere arbeidsmarktuitkomsten. Het is echter nog onduidelijk in hoeverre dit voor alle opleidingsniveaus geldt en of dit ook geldt voor meer conjunctuurgevoelige opleidingsrichtingen. De resultaten laten zien dat schoolverlaters uit meer specifieke opleidingsrichtingen vaker een loopbaan hebben die wordt gekenmerkt door een hoge mate van inkomenszekerheid in vergelijking met schoolverlaters uit meer algemene studierichtingen. Het effect van specificiteit is het sterkst voor schoolverlaters op mbo4 niveau, waar sterke banden met werkgevers worden gecombineerd met relatief hoge vaardigheden. Daarnaast, en in tegenstelling tot wat ik had verwacht, is het effect van specificiteit sterker voor schoolverlaters uit conjunctuurgevoelige studierichtingen.

In ***hoofdstuk 4*** analyseer ik een sociologische verklaring van loopbaanuitkomsten: beroepen. Ik ga na of het beroepsniveau en de soorten taken die in het beroep worden uitgevoerd bepalen of flexwerk vooruitzichten biedt of leidt tot precariteit. Het beroepsniveau en de soorten taken die bij een beroep horen bepalen namelijk in grote mate in hoeverre mensen in dit beroep vervangbaar zijn. Werkenden in beroepen die vaardigheden van een lager niveau vereisen en waarin routinematige taken worden uitgevoerd zijn makkelijker te vervangen en lopen hierdoor het risico op meer precaire carrières (Goldthorpe, 2007). Om dit te toetsen, koppel ik de typologie uit hoofdstuk 2 aan gegevens uit de Enquête Beroepsbevolking, waarin meer informatie staat over de beroepen van deze werknemers. Deze beroepsinformatie wordt vervolgens gekoppeld aan de O*NET database die informatie bevat over welke soorten taken in deze beroepen worden uitgevoerd. De resultaten tonen aan dat beroepen die vaardigheden op hoog niveau vereisen niet per se beschermen tegen een precaire loopbaan met een laag niveau van werk- en inkomenszekerheid. Routinematige taken leiden daarentegen niet per definitie tot precariteit, aangezien routinematige cognitieve taken positieve effecten kunnen hebben op de werk- en inkomenszekerheid, terwijl routinematige handmatige taken de werk- en inkomenszekerheid verminderen.

Ten slotte richt ***hoofdstuk 5*** zich op hoe de strategieën van werkgevers voor het gebruik van flexwerk – screening, aanpassingsvermogen of kostenreductie – de loopbaanuitkomsten van hun flexwerkers beïnvloeden. Screeningstrategieën hebben als doel om langdurige arbeidsrelaties te creëren en zouden dus resulteren in carrières met vooruitzichten. Aanpassings- en kostenreductiestrategieën hebben dit doel daarentegen niet, wat zou resulteren in meer precaire carrières voor hun werknemers. Door strategieën te definiëren als patronen in een stroom van beslissingen (Mintzberg, 1978), heb ik de strategieën die werkgevers hebben voor het gebruik van flexwerk afgeleid uit de manier waarop ze flexwerk gebruiken, zoals het aandeel flexwerkers, het aantal flexwerkers dat een vast contract krijgt, en overtollige mobiliteit van werknemers in het bedrijf. De resultaten laten zien dat werknemers in bedrijven met screeningstrategieën een loopbaan hebben met een hoger niveau van werk- en inkomenszekerheid, terwijl werknemers in bedrijven met kostenbesparende strategieën vaak een loopbaan hebben met een laag niveau van werk- en inkomenszekerheid. Interessant is dat de negatieve effecten van werken in een bedrijf met een aanpassingsstrategie beperkt bleven, met loopbaanuitkomsten die dichter bij die van werknemers in screeningbedrijven lagen dan bij die van werknemers in kostenbesparende bedrijven.

Door in dit proefschrift een procesgerichte benadering te gebruiken, heb ik kunnen aantonen dat er meer diversiteit is in uitkomsten van flexwerk dan voorheen werd aangenomen. Deze aanpak biedt dus kansen om vanuit drie verschillende perspectieven genuanceerder antwoord te krijgen op zowel oudere als nieuwere vragen over flexwerk. Alle drie de perspectieven geven inzicht in wanneer flexwerk vooruitzichten biedt, leidt tot precariteit, of iets daar tussenin. Aangezien het buiten het bereik van deze dissertatie viel om deze drie perspectieven te combineren, zou toekomstig onderzoek het samenspel tussen deze perspectieven kunnen onderzoeken om te zien wat het belangrijkst is bij het verklaren van loopbaanuitkomsten van flexwerk. Hoewel het gebruik van een procesgerichte aanpak enkele extra uitdagingen kan opleveren, bijv. rekenkrachtbeperkingen en methodologische overwegingen, kan ik toekomstig onderzoek ten zeerste aanbevelen om een vergelijkbare aanpak toe te passen.

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