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SPECIAL ISSUE PAPER

# Self-employment career patterns in the Netherlands: exploring individual and regional differences

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## Abstract

Although the self-employed represent 16.7% of the Dutch labor force (OECD 2020), their internal heterogeneity in profiles regarding motivations, characteristics and career trajectories remains unclear. Yet, understanding self-employment profiles and their spatial distribution may help understand differences in career progression of the self-employed. This study identifies and describes patterns in long-term career trajectories of the Dutch self-employed, and it explores spatial differences along the urban hierarchy. The study uses a life-course approach and register data of the whole population to find common patterns of careers among a sample of Dutch self-employed ($N$=42,028) and their spatial distribution. We investigated careers through sequence and cluster analysis of individuals' socio-economic statuses between 2003–2018. The analysis identifies 7 career clusters that collapse into three main career profiles: Mixed self-employment careers that combine self-employment with wage-employment, stable self-employment, and precarious self-employment. The clusters differ importantly in terms of the individual characteristics of the self-employed including age, gender, educational level and income. In terms of spatial distribution, the study shows that self-employment career profiles follow the urban hierarchy. Urban regions give way to all types of self-employment, while rural regions mainly exhibit stable self-employment. Precarious self-employment presents differently in urban and rural areas; in urban labor markets, we find self-employed individuals vulnerable to economic shocks, losing their jobs as a consequence of the financial crisis in 2007/08. In rural regions, formerly inactive workers become self-employed following the crisis.

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## 1 Research question and motivation

Self-employment plays an increasingly important role in the Dutch economy. With 16.7% of the Dutch labor force being self-employed in 2018 (OECD 2020), self-employment (SE) accounts for a substantial part of the Dutch GDP and employment. The current prominence of self-employment, in the Netherlands and elsewhere, coincides with modern labor market conditions favoring flexibility over job security in many industries, and career paths showing more job changes than ever before (Thörnquist 2015). This is supported by the spread of the platform economy which facilitates individuals of various crafts and industries to work as independent contractors or freelancers and thereby creates more diverse opportunities for self-employment on the labor market (Farrell and Greig 2016). This facilitation leads to a growing number of individuals from all professions and various starting points entering self-employment (Hoang et al. 2020), with that the group of the self-employed becomes increasingly heterogeneous (Bögenhold 2019). The sources of heterogeneity among the self-employed are manifold and have been addressed from various angles, e.g., via starting points (Carrasco 1999), sectors (Faggio and Silva 2014), motivations (de Vries et al. 2019) or terms of self-employment (Bögenhold 2019). Cieślik and Dvouletý (2019) present an overview of the recent research on segmentation of self-employment in which they show that a clear classification is often difficult to achieve. The diversification of self-employment and its respective career paths suggests that spells of self-employment should be understood in the context of the whole career rather than in a single spell of self-employment (Koch et al. 2019; Wilthagen and Tros 2004). Contextualizing a spell of self-employment in someone's career pattern allows for a more comprehensive understanding of the heterogeneity in self-employment and broadens the idea of self-employment success (e.g., via including career stability or volatility over time). Further, Hermanowicz (2007) stresses that taking time and place factors into account can provide a more accurate distinction between different career patterns and a more thorough understanding of individual differences. While part of the career is shaped by active choices and moves, the time and location of one's job opportunities can have an impact that goes beyond that of the chosen field of work (Hermanowicz 2007).

Our study aims to shed light on the heterogeneity of the self-employed via their long-term career trajectories. Following the proposition of Cieślik and Dvouletý, we investigate educational attainment and take into account hybrid forms of employment as well as the transition of the self-employment business into an employer as much as possible with the data obtained. With the longitudinal data available to us, we can conceptualize career success as the stability and duration of a career in (self-) employment. Taking into account the positions held before and after self-employment makes it possible to objectively classify different types of SE careers based on their development over time (e.g., in terms of stability/volatility) rather than the subjective motivation of the self-employed. In addition to our understanding of career success as relative career stability, we examine the income development across the observed period and thus use income as a second, more conventional measure of success.

Further, this study builds on the career perspective on self-employment and adds a regional dimension, which has mostly been overlooked so far. In addition to profiling Dutch self-employment careers, we seek to understand how career patterns of the self-employed vary regionally. Our interest in regional variation in self-employment careers stems from the observation of regional differences in the types of new businesses created, self-employment success, and its effects on regional economic growth (Andersson et al. 2016) as well as the varying effects of different regions on individual career paths (Hermanowicz 2007). There are two different scenarios of how the regional differences in self-employment careers arise. The first argues that people with the same skills and preferences tend to gather and reside in the same areas (Eliasson and Westerlund 2018). Consequently, regional clusters could be influenced by a self-selection, meaning that people with similar characteristics and careers choose to run their businesses close to each other. The second scenario argues that labor market conditions, which affect career opportunities directly, differ between regions. Hence, the regional context shapes the career decisions a person can take (see, for example, Liñán et al. 2011). In our analysis, we are able to disentangle both effects to some extent by simultaneously assessing the associations between personal characteristics and the career profile as well as a regional contextual factor.

We take the study by Koch et al. (2019) as our empirical starting point and extend it with a regional perspective. Koch et al. find four different career patterns following a sample of German self-employed over the course of 26 years. They show that persistent self-employment careers are linked to higher income and higher job and life satisfaction. This study aims to find comparable patterns among the Dutch population of self-employed, explore their characteristics and showcase how they are spread out geographically. In order to obtain comparable results, our analysis follows Koch and colleagues' approach in establishing career patterns. Also, we use income as indicator for career success. Apart from the specific geographical angle, we contribute to the state-of-the-art by performing the analysis on one of the largest samples of self-employed used in career research so far. For a 16-year period, we track the sequence of states of employment, using register data at the individual level. The resulting career sequences are summarized in a number of clusters, and their prevalence across the urban hierarchy is explored.

## 2 Theory and background

### 2.1 Self-employment in the career

Self-employment can take place in different periods throughout a career, all differently related to motives to become self-employed and the success people experience. The positions held before and after self-employment have been studied before but mainly focused on singular transitions in and out of self-employment (Luzzi and Sasson 2016), and the benefits or trade-offs that come with it. From this, we learn that self-employment entries from different starting points are associated with different conditions and risks (Carrasco 1999). Explicitly, individuals entering self-employment from unemployment show higher business failure rates than the ones entering from wage-employment. Further studies have shown women and or lower educated individuals to be at higher risk for precarious career paths (Struffolino 2019). A stable starting position and relevant experience allow individuals to only enter into self-employment when they expect a good pay-off.

The position of self-employment in the career is a valuable conceptualization of success or the role of self-employment in a career. At the same time, the career is influenced by underlying individual and contextual variables. These include age (when entering into self-employment), gender, work experience, industry, type of (self-)employment, motivation and human capital or social networks (Schellenberg et al. 2016; de Vries et al. 2019). Most research on self-employment careers classifies the self-employed in terms of their motivational determinants as opportunity or necessity self-employed (Acs 2006; van der Zwan et al. 2016; Fairlie and Fossen 2020). If explicit measures of motivation are unavailable, pushed and pulled self-employment can also be distinguished by a person's career over time via their socio-economic status. Self-employment after a spell of unemployment, for example, is more likely to be pushed than pulled. Thereby, career patterns give us valuable information about job security, stability and flexibility via the number of transitions and the lengths of spells as well as the position on the labor market preceding self-employment. From this, we are able to infer the voluntariness of career choices. Stable patterns with long spells of self-employment can indicate a voluntary self-employment career, whereas fickle patterns with many transitions between different states of employment hint at necessity self-employment.

As previous research shows, some groups are more at risk for precarious employment conditions or self-employment patterns than others (Struffolino 2019). In particular, lower-educated women have a higher chance to end up in precarious career paths, showing that education and experience are important for obtaining a stable (self-employment) career. The same factors are thought to facilitate smooth transitions between various states of employment or different jobs. As a consequence, individuals with poorer starting conditions have a lower chance of experiencing upward social mobility throughout their career. A successful self-employment career could be a way for individuals with lower education to climb up the social ladder. As a person with a better starting position would not have the same struggle, a stable self-employment career would be subjectively more impactful and motivating for the individual coming from poorer conditions (Hermanowicz 2007).

### 2.2 The regional context and self-employment careers

Next to factors discussed above, external factors also influence self-employment decisions and careers. On the motivational side, the social valuation of self-employment can affect the choice to become self-employed so that regions with a more positive view on self-employment show higher start-up rates (Liñán et al. 2011). On the performance side, regional factors can affect the longevity of a self-employment business. Andersson and Koster (2011) show that regional characteristics, such as the average educational level, the employment rate and the level of local start-up activity, influence the persistence of new firms and thereby impact career trajectories of the self-employed. Regions with a higher start-up density exhibit stronger firm persistence, showing that individual SE career trajectories in close proximity can affect each other. Moreover, Faggio and Silva (2014) found that higher rates of self-employment positively link to high firm creation rates and innovation in urban areas but not in rural ones. They explain this by urban workers being more directly affected by local labor market conditions and the rural self-employed being less vulnerable to local economic fluctuations.

Regional differences in self-employment careers may be interpreted in two distinct ways. On the one hand, the differences may be rooted in the regional context influencing the progression of careers. On the other hand, there may be geographical sorting of self-employed with certain careers. More explicitly, regional variation in career patterns could be attributed to differences in economic opportunities and local labor markets (Faggio and Silva 2014) including regulative and institutional differences. In the analysis, we focus on the role of agglomeration in the career patterns found. Agglomeration has been shown to improve labor market outcomes. Notably, agglomeration economies lead to higher job mobility because of thicker labor markets, leading to better matches (Eriksson et al. 2008; Abel and Deitz 2015). This suggests that self-employment careers in agglomerated areas combine self-employment with other positions on the labor market more often. With other jobs more readily available, the self-employed may be able to move in and out of self-employment at suitable moments in their career. However, the high competition on urban labor markets may also result in many volatile and precarious self-employment careers. Also, flexibilization phenomena, such as the platform economy, are more typical of urban areas and may induce high levels of precarious self-employment (Thörnquist 2015). Again, spatial sorting of careers may play a role here as the positive effects of urban agglomeration economies may come at a cost for rural regions losing business and human capital (Partridge and Rickman 2008). It is therefore important to assess the role of agglomeration net of the individual characteristics of the self-employed.

The career perspective on self-employment extends the measurement of self-employment success over a longer timeline. It allows for career characteristics like volatility to be part of the concept of success and thereby enriches our understanding of self-employment success. Nevertheless, identifying causal relationships between pre-self-employment characteristics and post-self-employment outcomes is more complicated as both are assessed simultaneously. Analyses on self-employment careers are more explorative than they are causal. Yet, the development of careers can be linked to other success measures, e.g., the development of income (Koch et al. 2019). People with more stable career patterns will rather show a positive income development as more time spent in one position means improving the skill set, market knowledge and network needed to succeed in the job (Cooper et al. 1994; Balcar 2014). Also, to understand the structuring effects of location and agglomeration, its role should be analyzed net of individual characteristics, including sex, age and level of education, that then account for possible spatial sorting.

# 3 Methods

## 3.1 Sequencing careers

In order to reveal profiles of the Dutch self-employed, we first document the yearly socio-economic statuses of a sample of people on the Dutch labor market with at least one spell of self-employment in the study period. The consecutive statuses are then analyzed in a sequence analysis that clusters careers with similar patterns. Once these clusters have been established, we characterize the clusters in terms of socio-demographic information and explore the geographical dimension in the clusters. We first take a univariate approach and conclude with a multinomial logit model to account for interference between the individual variables and possible spatial sorting across the urban hierarchy.

## 3.2 Identifying self-employment careers

The data used for all analyses are individual-level register data (microdata) that were provided by Statistics Netherlands.[1] These include all people in the Netherlands and document income, socio-demographic information including the residential location, educational activities and the position on the labor market (socio-economic status) from 2003 to 2018. This is the most recent and the longest continuous period of data available.

From the data, we extract the socio-economic status (SES)[2] and the sequence of SES characterizing the self-employment careers. The SES includes seven distinct categories: Education, wage-employment, self-employment,[3] director or major shareholder of a firm, retirement, unemployment, and inactivity on the labor market. The SESs for all persons have been obtained via yearly tax registry data. A person's SES is defined by the one activity generating the majority of their income, or, respectively, their enrollment with an educational institution. Thus, we cannot identify parallel part-time self-employment and wage-employment, for example.

Before 2011, a person reporting any form of income from self-employment was classified as self-employed. Therefore, individuals having a second income from self-employment on the side have been counted as self-employed up until 2010. Starting in 2011, the main source of income of a person is the crucial factor in determining the SES. This change of definition will show in self-employment careers of individuals running small businesses on the side or working in self-employment on a project basis. It may thus inform some jump in the data in the years 2010/11. Given the precise change these jumps may even be informative to the nature of self-employment, i.e., relatively small-scale. Though visible, the jumps do not heavily

[1] https://www.cbs.nl/en-gb/our-services/customised-services-microdata/microdata-conducting-your-own-research.

[2] The SES is determined yearly, in December until 2010, in January since 2011.

[3] This encompasses entrepreneurs, solo-self-employment, freelancing as well as any other type of self-employment. The special case of freelancers is addressed later in this paper.


**Fig. 1** Exemplary visualization of career sequences. Different shades of gray represent the SES, and each segment between two vertical lines represents one year. Sequences are created by arranging the SES chronologically for each individual

influence the outcomes of the sequence analysis as individual cases and their transitions only have a limited value in explaining the career cluster.

For the purposes of our analyses, we select only those that have at least one year of self-employment experience in the 16-year period under investigation. Further, to ensure that we examine the active working population, the sample was restricted to everyone who was of working age ($\geq$ 18 years) in the first year and not older than 68 years in the last year of measurement. Additionally, data had to be available for the whole period of 16 years. People who deceased, emigrated from or immigrated to the Netherlands during the observed period of time are not included in the sample. Finally, the relevant population for our analyses consists of 1.4 million persons ($\approx$ 12% of the Dutch potential labor force). Due to limits in data processing inherent to the algorithm and computation power available, we performed our analyses on a random subsample of 3% of the population which has been drawn by the random subsampling function in SPSS, leading to an N of 42,028. We controlled our results for robustness with two more random subsamples of the same size. The sequence length of 16 years is similar to most comparable studies (Kovalenko and Mortelmans 2014; Koch et al. 2019), and our data set is one of the largest ever used for a sequence analysis in a social science.

### 3.3 Sequencing and analysis

With the data in place, we can identify the careers patterns of Dutch self-employed. Figure 1 illustrates the set-up of the dataset as a collection of individual sequences.

The optimal matching sequence analysis reveals common patterns in self-employment careers. This method originates from biogenetic research (Abbott and Forrest 1986), but it has grown popular among researchers for studies on career development (e.g., Biemann et al. 2012; Middeldorp 2016; Koch et al. 2019). It allows for sequences of categorical data to be assessed based on their similarity to each other and then clustered in groups. Dlouhy and Biemann (2015) provide an overview of best practices in clustering methods, and we base the sequencing and optimal matching analyses on their suggested approach. The sequence and subsequent cluster analyses have been performed in R Studio with the TraMineR and cluster packages. Below, we explain the sequencing procedure in more detail.

Using the categorical data of the SES over the years, a career sequence was created for every individual with a length of 16 points of measurement. Working with the same sequence length for every individual ensures easy comparability and renders defining insertion and deletion costs unnecessary. After combining the data points into sequences, the transformation costs were defined to carry out the optimal matching of sequences. Transformation costs represent the number of transformations (i.e., deletion, insertion or substitution) it takes to transform one individual sequence into another one. The sequences are matched based on the order of SES and the number of transitions occurring. We estimated the transformation costs using the observed transition rates for all possible transitions between the socio-economic states. Based on this, a substitution matrix was created. Then, the optimal matching analysis (OMA) of all individual career sequences was conducted. This algorithm compares sequences of categorical data based on their similarity to each other using the fewest possible transformations. In the clustering process, Ward's method was used, meaning hierarchical clustering is carried out with the aim to minimize the within-cluster variance while maximizing the distance between the clusters. Ward's method was chosen as it is especially robust to noisy data (Dlouhy and Biemann 2015) which this study is expected to have because of the increasingly blurred lines between individual types of employment. The clustering led to a cluster tree which allows for determining the optimal number of clusters. As in traditional cluster analysis, identifying the exact number of clusters is to some extent subjective. On the basis of the cluster membership plots, cluster stop indicators and the characteristics of the clusters, a seven-cluster solution best characterizes the career patterns in our data set. These seven clusters collapse into three overarching self-employment career types.

### 3.4 Individual and regional characteristics

Using socio-demographic data, we can characterize the clusters of self-employment careers both in terms of success measures (income) and in terms of socio-demographic characteristics including geography. Income data included in our analyses reflect the gross annual personal income from labor or self-employment. Income from labor and income from self-employment might not be seen as the exact same measure. However, we combine them considering that we focus mainly on understanding the career patterns and their characteristics instead of measuring (financial) success. Self-employment comes with various opportunities for tax breaks, which might lead to a depressed reported income. To ensure that our data are reliable, we compare the income distribution to the income indices for wage employment as well as self-employment for the whole Dutch population and find no differences between our data and the general population.

We further characterize the career clusters in terms of age-structure (in 2018), sex, educational attainment and the most recent residential location. Additionally, to address the broad sectoral heterogeneity in self-employment and the different contract types or working conditions, we explore the share of freelancing per cluster in 2018 as well as the sector of the last self-employment spell. Data on age and sex were available for every person. The residential location was missing for 8 individuals evenly distributed across clusters, and thus, we excluded them from our analyses. The highest educational attainment measured in the levels of primary, secondary, or vocational education, bachelor's degree, and master's or doctorate degree was also included in the cluster characterization. It is determined by surveys in earlier years and, more recently, the registered degrees from educational institutions. The educational data are only available for 55% of the sample. Moreover, the data available are probably upward biased, as the relative ease of tracking higher educational qualifications skews the distribution toward higher education levels. Thus, we use the educational data only to describe the clusters.

In addition to the individual characteristics, we included the degree of urbanity of the residential locations to explore the association between the spatial context and self-employment careers. Urbanity is measured on a three-point scale, urban, intermediate and rural, measuring the number of other addresses within one-square-kilometer around the respective address. An urban location has more than 1,500 surrounding addresses in this radius, the intermediate level has 500–1,000, and urban regions have less than 500. However, we only measure the location, and therefore the urbanization level, at the end of our observed period. Any interpretation of the locational effect needs to take into account that we do not observe spatial mobility. A multinomial logistic regression was used to unravel the associations between the individual characteristics, the degree of urbanity and cluster membership. The level of urbanity, age, sex and level of income in 2003 functioned as predictor variables for the odds ratio of membership of the career clusters.

## 4 Results

### 4.1 Cluster descriptions and characteristics

Figure 2 summarizes the seven clustered career patterns derived from the sequence analysis. The plots show the distribution of the socio-economic statuses

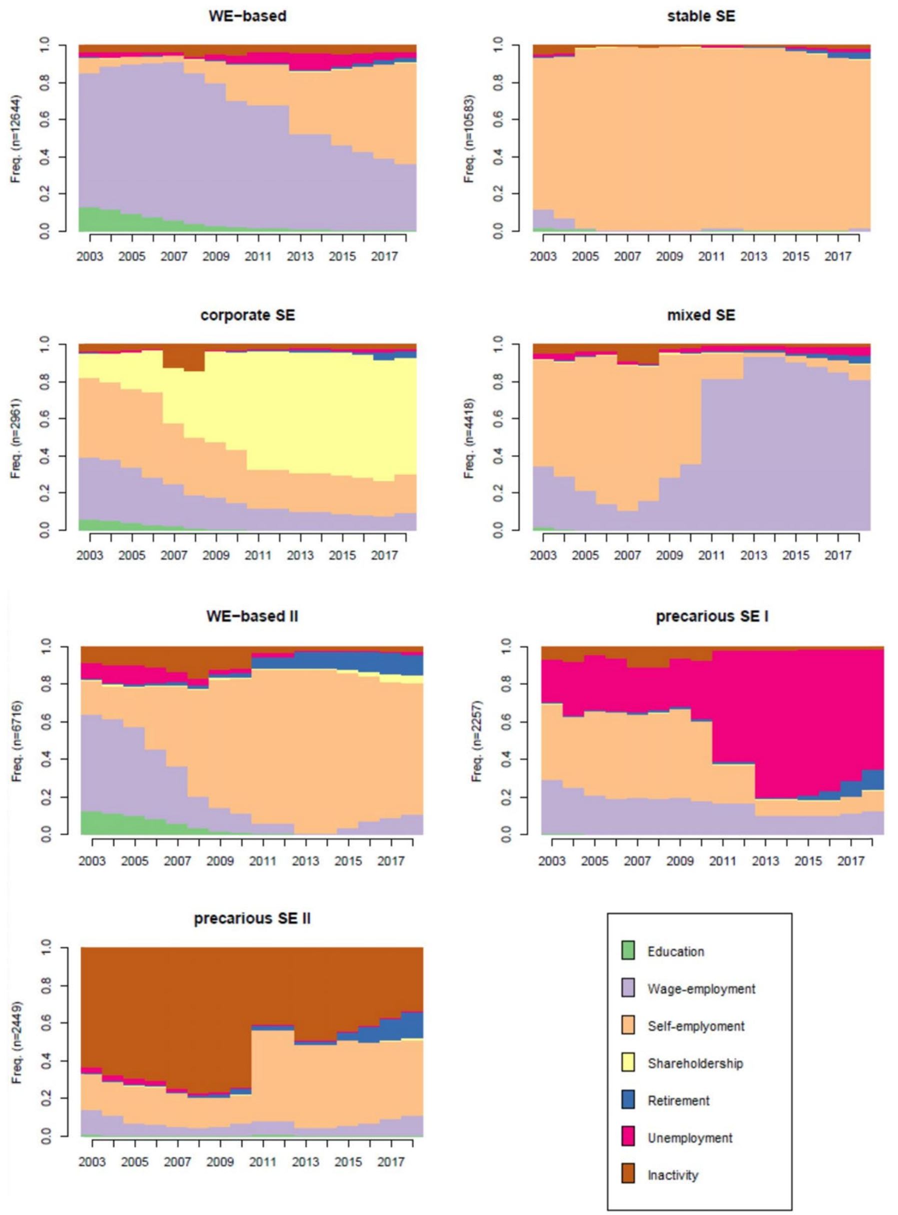


**Fig. 2** Sequence plots for the career clusters, time plotted on the x-axis, frequency of cases plotted on the y-axis, colors representing different SES

across each cluster between 2003 and 2018. For every year (vertical lines), they show the share of people in the cluster with a certain SES. Sequence index plots, in which each horizontal line shows an individual career, are available in the Appendix (Fig. 4).

**Table 1** Clusters of self-employment career patterns and respective characteristics

| Cluster | N | % | Name | % Male | Age in 2018 | % Bachelor/ master | Income 2003 (€) | Income 2018 (€) | % free-lance in 2018 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 12,644 | 30.1 | WE-based SE | 51.8 | 47.0 | 49.7 | 21,500 | 34,192 | 6.4 |
| 2 | 10,583 | 25.2 | Stable SE | 67.3 | 54.1 | 48.5 | 23,573 | 33,052 | 0.7 |
| 3 | 2,961 | 7.0 | Corporate SE | 79.6 | 51.3 | 67.2 | 40,902 | 55,420 | 2.1 |
| 4 | 4,418 | 10.5 | Mixed SE | 60.6 | 52.2 | 42.8 | 25,058 | 39,446 | 0.6 |
| 5 | 6,716 | 16.0 | WE-based SE | 55.3 | 49.7 | 46.6 | 19,876 | 31,626 | 5.7 |
| 6 | 2,257 | 5.4 | Precarious SE I | 58.2 | 54.6 | 21.3 | 17,322 | 16,768 | 1.8 |
| 7 | 2,449 | 5.8 | Precarious SE II | 15.8 | 55.4 | 26.2 | 8,262 | 10,343 | 22.4 |
| Total | 42,028 | 100 | | 57.4 | 51.0 | 46.3 | 22,451 | 32,901 | 4.6 |

**Table 2** Distribution of career clusters across sectors

| | Agriculture | Construction, manufacturing | Wholesale, retail | Hotel & catering, transport, couriers | Administrative and business services | Education, government | (Health) care, sports, culture | Other, foreign businesses |
|---|---|---|---|---|---|---|---|---|
| WE-based | 3.1 | 16.1 | 13.1 | 8.0 | 30.2 | 5.0 | 22.4 | 2.1 |
| Stable | 15.4 | 18.3 | 17.3 | 9.5 | 17.0 | 2.7 | 18.7 | 1.1 |
| Corporate | 4.0 | 12.8 | 16.5 | 6.4 | 39.2 | 1.7 | 9.9 | 9.5 |
| Mixed | 6.2 | 10.9 | 16.3 | 9.6 | 28.4 | 4.1 | 16.0 | 8.5 |
| Precarious I | 3.8 | 16.9 | 20.1 | 13.2 | 16.1 | 3.5 | 15.2 | 11.2 |
| Precarious II | 10.5 | 11.5 | 19.7 | 9.6 | 15.4 | 3.2 | 22.4 | 7.7 |
| Total | 7.6 | 15.5 | 15.7 | 8.9 | 25.5 | 3.8 | 18.9 | 4.2 |

**Table 3** Distribution of all clusters across the three levels of urbanity

| Cluster | N | Name | % Urban | % Intermediate | % Rural |
|---|---|---|---|---|---|
| 1 | 19,360 | WE-based SE | 52.4 | 16.2 | 31.4 |
| 2 | 10,583 | Stable SE | 40.8 | 16.4 | 42.8 |
| 3 | 2,961 | Corporate SE | 45.6 | 19.8 | 34.6 |
| 4 | 4,418 | Mixed SE | 47.9 | 16.9 | 35.2 |
| 5 | 2,257 | Precarious SE I | 57.0 | 13.4 | 29.6 |
| 6 | 2,449 | Precarious SE II | 42.5 | 17.1 | 40.5 |
| Total | 43,028 | | 48.2 | 16.5 | 35.3 |

A Chi-square test indicated a significant correlation between cluster type and the urban hierarchy: Pearson $\chi^2 = 602{,}967$, $p < .001$

The characteristics of each cluster (Table 1), the cluster distribution across sectors (Table 2) and different levels of urbanity (Table 3) are also depicted below. It is important to stress that the different characteristics of the people in the clusters cannot be interpreted as causal factors for having a certain self-employment career profile. Rather, they document exposure to careers, indicating the relevance of certain self-employment careers for certain groups. This may open up avenues for additional research, but also identify target groups for policies, particularly when it comes to the more precarious self-employment careers.

The first cluster shows the transition from a long spell of wage-employment to self-employment for the majority of the group. Thus, we named the group *WE-based SE careers*. As the largest group of the sample, it represents the most common route into self-employment. Experience and resources are built as an employee and then capitalized upon in self-employment.

The second cluster, which is the second largest, displays *stable self-employment careers*. These are characterized by long-term, continuous self-employment with few changes in SES over time and high career stability.

The third cluster is rather small, as it comprises individuals transitioning from self-employment into shareholdership. Although we cannot follow the firms, the pattern suggests SE careers in which the firm is bought or incorporated with the original owner taking a shareholder position. Consequently, we named this pattern *corporate SE careers.*

The fourth cluster, similar to the first, combines wage-employment with self-employment. But rather than being consecutive, the distribution suggests that SE and WE are alternated. The spike in 2011 resulting from the definitional change in self-employment also suggests this pattern shows *mixed* or *hybrid self-employment,* which we cannot definitely disentangle because the data only allow for one SES at a time. Particularly those with small self-employment endeavors are affected by the change in definition.

The fifth cluster shows the same pattern as the first cluster, from a short spell of wage-employment to longer spells of self-employment. So, this career pattern seems to be the continuation of cluster one later in the career of the self-employed initially working in WE. Therefore, this cluster was also named *WE-based SE careers.*

The sixth cluster is the smallest and displays long spells of unemployment paired with brief spells of self-employment; we named it *precarious SE careers I.* A substantial part of the cluster loses their jobs most likely due to business failure or bankruptcy in 2010–2013, shortly after the global economic crisis. This could indicate this group is especially vulnerable to acute economic shocks. This pattern has been exacerbated by the definitional change of SE that downplays the role of fringe self-employment.

The last cluster, the second smallest, shows long-term inactivity interrupted by short spells of self-employment, with many individuals transitioning into SE in 2010/11. Even though the sudden increase in SE in this cluster coincides with the definitional change, it seems unlikely that it is caused by the change in definition. Before 2011, it was easier to be classified as self-employed. Nevertheless, we see individuals picking up self-employment mainly in 2011. Since the definitional change does not offer a good explanation for this trend, it might be a delayed effect of the economic crisis. This cluster was named *precarious SE careers II.*

Table 1 documents socio-demographic characteristics of the self-employed in the clusters, including age, gender, educational level and median income as commonly used predictors of the incidence and the success of self-employment. Income has a double interpretation. It is an explanatory variable for entering self-employment. A higher income, and thus likely a higher seed capital, provides more opportunities for self-employment. At the same time, it is an indicator for success, particularly when assessed over time. Note, that we cannot meaningfully include information that fluctuates over the course of a career, such as sector information. However, to still get some insight into the sectoral heterogeneity in SE careers, we explored the distribution of clusters across sectors for the most recent spell of SE. The share of cluster members working as freelancers in 2018 has been included to get an impression of the self-employment conditions per cluster, showing a strikingly high percentage of freelancers (22.4%) in the second precarious SE cluster.

The clusters show meaningful differences between them, which are in line with the conceptual distinction between successful and precarious careers and the people that are associated with both. In terms of gender, men are overrepresented in most clusters mirroring the overrepresentation of men in self-employment in general. This especially shows in careers with an element of self-employment throughout (Clusters 2 and 3). The clusters that show more mixed careers (Clusters 1, 4, 5, 6) have a more even gender balance. Strikingly and rather disconcertingly, women are overrepresented in precarious self-employment that combines labor market inactivity with self-employment (Cluster 7). This then—using a different approach—corroborates the earlier findings by Struffolino (2019). One contributing factor to this is the women's overrepresentation in sectors like care and health services, which see a lot of involuntary self-employment which contributes to rather precarious self-employment careers. The inactivity may also reflect life course events including raising a family. Self-employment may be a route back into the labor market then. However, returning to the labor market is just a small success regarding the low income and high volatility in this career cluster.

The age distribution across the clusters is in line with the understanding that both WE-based career patterns represent the same career trajectory just a few

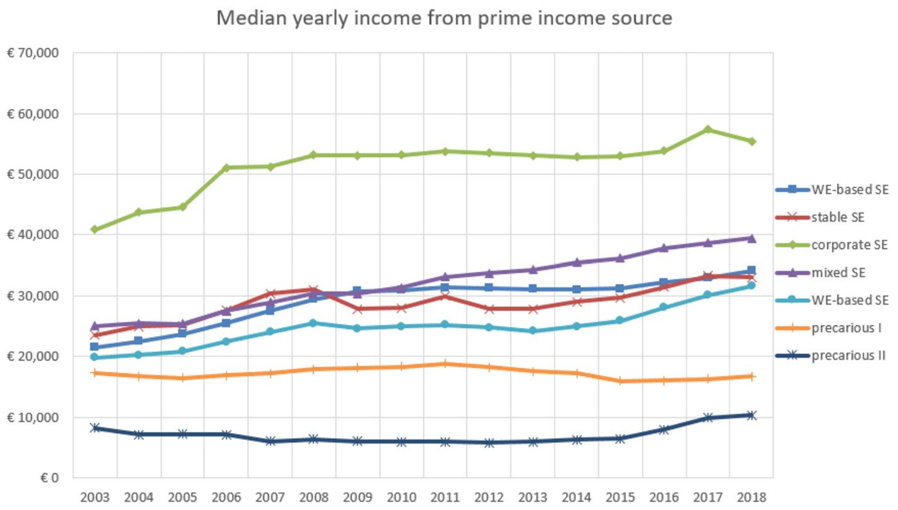


**Fig. 3** Income development per year and cluster based on median income per cluster

years apart. Therefore, to facilitate further analyses and interpretation of the results, clusters 1 and 5 are collapsed into one career pattern that combines wage-employment with subsequent self-employment. This will be referred to as WE-based careers in the remainder of this paper. Furthermore, the age distribution confirms the intuition about the most vulnerable demographics. The precarious self-employment careers (Clusters 6 and 7) include the eldest people (in 2018). The other clusters do not differ very much in terms of age. Cluster 1 (WE-based SE careers) is the youngest cluster with an average age of 47 years in 2018.

In terms of education, the more stable careers and the ones that combine WE with SE present with relatively higher educational attainments. The more volatile careers are more prevalent among people with a lower educational attainment.

Table 1 documents the gross yearly income at the beginning of the period and at the end. Figure 3 shows the development across the whole period based on the median income per cluster and year. All income indices per year are in line with the statistics for the whole Netherlands as well as all Dutch self-employed in all respective years (CBS 2020). The average in our data is marginally lower due to individuals working in wage-employment, receiving benefits, or a pension being part of the sample. The diagram shows both year effects (including the crisis in 2008) and experience effects from developing careers. Most clusters show a positive trend. There are striking differences, however, in the success of the career profiles. In terms of income levels, cluster 3 (Corporate SE careers) is the most successful. The precarious careers have the lowest incomes throughout and a plateau phase or negative trend almost returning to the initial income level in the last years of our observation. The income in the career profiles with the most prominent role for self-employment—WE-based SE careers, stable SE and corporate SE careers—plateaus between 2008 and 2015/16. Interestingly, the income development in cluster 4 (mixed SE careers) hardly seems affected by the crisis. In the SES-distribution for that period (Fig. 1), we see that a relatively large share in this cluster managed to leave self-employment for wage-employment.

The distribution of cluster members across different sectors in 2018 is shown in Table 2. This information helps further understand the heterogeneity of self-employment in our sample. Relatively many individuals in stable SE work in agriculture, the corporate self-employed mainly work in business or financial services. The precarious SE careers are overrepresented especially in retail (precarious I) and healthcare (precarious II). However, with adding the sectors the number of subpopulations below the critical threshold for zero-cell populations in a multinomial logistic regression becomes too large for the model to be reliable (5% based on approaches by Agresti 2003; Hosmer and Lemeshow 2000). This means there would be too many combinations of variable levels that are not observed in our data. Thus, we cannot include the sector information in our multinomial logit model.

### 4.2 Regional distribution

Turning to the regional pattern, we explore the distribution of the clusters across the urban hierarchy. The location data are measured in 2018. This implies that the location cannot be interpreted as being causal for the career pattern, it rather shows which areas are faced with certain self-employment career profiles. The distribution of SE career patterns across the level of urbanity is based on data of the residential location of the self-employed on the municipal level.

Table 3 shows the distribution along the three levels of urbanity, giving insight into how agglomeration is associated with self-employment careers. A chi-square test showed a significant association between these two factors (Pearson $\chi^2 = 602{,}967$, $p < 0.001$). Via z-tests, all following reported differences were found to be significant at the $p < 0.05$ level. On the urban level, all clusters showed occurrence rates that were significantly different from each other, except for precarious SE II. Cluster one is more prevalent in urban municipalities while being slightly underrepresented in rural areas. Stable SE careers are more widely spread in rural regions and less common in urban ones. This might be a consequence of a lack of competition and other job opportunities in rural regions. The corporate SE careers are overrepresented in intermediate areas. The two precarious SE career patterns show trends in opposite directions. The first precarious cluster presents as an urban phenomenon, while the second precarious cluster is underrepresented in urban regions and overrepresented in rural ones. This underlines that precarious careers are present in different settings and economic crises affect them differently depending on these settings.

### 4.3 Multinomial logistic regression

To assess the impact of all characteristics on cluster membership, we perform an explorative multinomial regression analysis. This allows us to some extent to

**Table 4** Multinomial logistic regression results, dependent variable: SE career clusters; stable SE is the reference group, reference categories per independent variable are indicated, standard errors are reported in brackets below the odds ratios

| | WE to SE | Stable SE (ref. group) | Corporate SE | Mixed SE | Precarious I | Precarious II |
|---|---|---|---|---|---|---|
| *n* | 18,488 | 10,157 | 2,876 | 4,234 | 2,116 | 1,356 |
| Age | | | | | | |
| > 33–44 | 6.257* (.039) | ref | 4.913* (.067) | 1.868* (.056) | .763* (.072) | .540* (.095) |
| > 45–56 | 1.689* (.030) | ref | 1.685* (.050) | 1.320* (.041) | .654* (.053) | .548* (.066) |
| > 57–68[a] | – | – | – | – | – | – |
| Sex[b] | 2.020* (.029) | ref | .839* (.054) | 1.486* (.040) | 1.214* (.052) | 5.667* (.074) |
| Income in 2003 | | | | | | |
| > below 11,100 € | .837* (.042) | ref | .165* (.074) | .690* (.060) | 2.936* (.089) | 4.894* (.113) |
| > 11,100–20,900 € | .723* (.042) | ref | .125* (.079) | .777* (.058) | 3.404* (.086) | 1.599* (.124) |
| > 20,900–39,000 € | 1.092 (.037) | ref | .300* (.054) | 1.124 (.042) | 2.412* (.084) | 1.189 (.128) |
| > above 39,000€[a] | – | – | – | – | – | – |
| Urbanity | | | | | | |
| > Urban | 1.679* (.029) | ref | 1.312* (.049) | 1.422* (.041) | 2.060* (.054) | 1.259* (.066) |
| > Intermediate | 1.289* (.038) | ref | 1.353* (.061) | 1.208* (.054) | 1.232* (.077) | 1.160 (.087) |
| > Rural | – | – | – | – | – | – |
| Observations | 43,028 | | | | | |
| $Chi^2$ | 8,729.186* | | | | | |

[a]Reference level within variable

[b]Reference category: male

*$p < 0.01$

account for spatial sorting of self-employed with certain characteristics connected to their career profiles. The model identifies the differences between the characteristics of the clusters relative to a reference cluster, the stable self-employment career (Cluster 2).

The variables included in the analysis are the same as in the descriptive analyses. Solely educational attainment was dropped as this information is only available for 55% of the sample. To ease interpretation, age has been re-coded into three groups: individuals in their early career years in 2003, the ones nearing retiring age in 2018 and a group in between. Also, income has been divided into four groups following the Statistics Netherlands classification of income in 2003. Results of the multinomial regression are presented below in Table 4 in form of odds ratios (OR) and standard errors. The odds ratios show the propensity of people with a certain characteristic being in a certain cluster, compared to the reference cluster. Odds ratios above one indicate an overrepresentation, odds ratios below one a relative underrepresentation. All values relate to the stable SE career pattern as reference group and the respective reference level per factor. Age, sex, income in 2003, and urbanity have all been found to be contributing to shaping SE careers over time ($\chi^2$ (40, $N = 42{,}028) = 8{,}729.19$, $p < 0.001$), suggesting the model as a whole is valid.

The distribution of characteristics across the clusters mimics the patterns found in the descriptive analysis. We see that relatively young people are more likely, relative to having a stable self-employment career, to be in careers that combine self-employment with wage employment. Older people are more likely to experience precarious self-employment careers. Women are 5.667 times more likely to be in the risk-driven precarious SE cluster over the stable SE career compared to men and 16.1% less likely to have a corporate SE trajectory over a stable one (OR 0.839). This suggests that female self-employment less often leads to flourishing self-employment careers and women are at a higher risk to take up self-employment as a reaction to certain labor market developments. Income has a double interpretation representing a success factor and also an enabling factor to enter a certain self-employment career path. By including the income at the start of the period (2003), we stress the latter interpretation even though some of the careers are already underway preventing us from disentangling both interpretations fully. People in the lowest income group in 2003 are much more likely to have a precarious SE career over stable self-employment (OR 2.936 and 4.894 for clusters 5 and 6, respectively). At the same time, they are 83.5% less likely to be corporately self-employed over steadily so when compared to the highest income group (OR 0.165). In short, initial income is highly indicative of the type of self-employment career for years to come.

Finally, we address the distribution across the urban hierarchy. Again, this cannot be interpreted as causal, but since the model controls for individual characteristics, the found associations are net of the spatial sorting in terms of age, gender and income. Even after factoring in spatial sorting to some extent, there still is an effect of the regional context. With rural areas and the stable self-employment careers as references, we see that all reported odds ratios are above 1 and significantly different from the reference except for the intermediate level of urbanity in the risk-driven precarious SE cluster. Consequently, for most clusters on the urban and intermediate level individuals are more likely to follow career patterns other than stable SE when compared to rural regions. This is in line with the descriptive findings and suggests the presence of regional variation in career patterns. Final conclusions on the impact of regional contexts, however, can only be drawn with further research.

## 5 Discussion

In this exploratory study on Dutch self-employment career patterns, we find seven distinctive career patterns which collapse into three archetypical self-employment careers. First, there are stable careers in which long spells of self-employment are the norm. Second, there are intermittent self-employment careers in which spells of wage-employment are alternated with spells of self-employment. Third, we find precarious careers in which self-employment is typically combined with unemployment or inactivity on the labor market. This finding is in line with previous studies that all show similar career pattern classifications, finding four to six different patterns, based on German and Belgian data (Biemann et al. 2012; Kovalenko and Mortelmans 2014; Koch et al. 2019). The study by Koch et al. (2019) is the only one that specifically addresses self-employment careers and concludes four patterns. Our characterization of career clusters is consistent with that but somewhat more detailed thanks to our differentiation of socio-economic statuses. We interpret our clusters with regard to the characteristics of the region, the personal characteristics of the individual and the career stability.

Mixed self-employment careers are the most prevalent type in the Netherlands making up 56.6% of the careers explored. This is in line with the observation that labor market experience and the acquisition of relevant skills are a main driver of self-employment and its success (Oberschachtsiek 2012). Coming from a stable position of wage-employment, people have financial security to plan and seek out business opportunities that match their professional background and skill set, thus making a successful transition more likely. Interestingly, the income development of the mixed self-employed appears only moderately influenced by the financial crisis of 2007/08. It seems as if the mixed nature of these careers allowed the self-employed to be flexible in handling challenges in labor markets by relying more on the either the more secure or more successful career option in case of real hybrid self-employment. For individuals with intermittent experience in wage- and self-employment, and skills accumulated in both, job opportunities might be more readily available despite the crisis. The smooth transition seems to indicate the self-employed possess skills that are easily transferable and in demand (Schaffner 2011). Mixed self-employment careers are more prevalent in the urban areas of the Netherlands which offer thicker labor markets and therefore further facilitate smooth transitions. In other words, urban areas allow people to be flexible in the self-employment career and thus promote the agglomeration of mixed careers. Since location is only measured at the end of our observed period, it cannot be precluded that the self-employed coming from wage-employment move to urban regions to start a business, although research suggests that individuals typically start a business close to their residential location (Koster and Venhorst 2014).

Stable self-employment careers are the second largest group (32.2%) and typical for somewhat older, male self-employed in rural areas. This is in line with previous findings of lower self-employment exit probabilities for self-employed in rural Finnish areas (Haapanen and Tervo 2009). A possible explanation for this is a lack of alternative job opportunities in rural regions. Many rural self-employed might rather be pushed into self-employment. Still, our method of assessing the locational data does not allow us to dismiss either possibility. A third explanation is that a nonnegligible part of this group of self-employed works in agriculture and is constrained to rural locations based on the position of their farmland. The group of self-employed in agriculture is important but not big enough to outnumber the other sectors and distort our results. Mainly for individuals not in the agricultural sector, location choice is also associated with personal characteristics. We controlled for those and they do not differ significantly from the other career clusters. Further research observing spatial mobility linked to SE entry would be relevant to understand the agglomeration of stable SE in rural regions. The income situation of stable self-employed is relatively good, particularly for the 7% of them that we label corporate self-employment careers. Generally, the corporate SE career seems to be the most (financially) successful, and also the one with the highest income in 2003. Thus, this cluster could comprise individuals who have been running their business very successfully with high returns on investment, so they could grow them into an incorporated firm (Fairlie and Fossen 2020). Another possibility is that the self-employed in this cluster started their SE careers from a better financial point than members of the other clusters with more capital to invest (Cooper et al. 1994). The effect of the economic crisis on the average incomes of these groups seems to be present with income levels plateauing after the crisis.

Precarious self-employment careers account for 11.2% of the careers observed. The profile of precariously self-employed complements the existing descriptions of demographics endangered by precarity: somewhat older, predominantly female and with lower educational attainments. It is disconcerting to see that the average income of this group remains stable across the entire study period, showing no increase over the course of their career. This underlines the importance of education for social upward mobility.

There are two distinct profiles within the group of precarious self-employment careers. The first one combines unemployment with spells of self-employment, particularly after the crisis of 2007/08. Instead of finding a stable job in wage-employment when their business is endangered by the crisis, a substantial part of this group ends up unemployed. Another part of the group remains in precarious SE with lower-than-average income. It seems as if the skills of these individuals do not fit the demand of the labor market during the time of the crisis; hence, they cannot find other employment easily. This interpretation is underlined by the facts that we mainly find this pattern in urban regions with diverse labor markets and that individuals with this career pattern have a relatively low level of education. However, further research is necessary to determine whether a lack of certain skills and a resulting mismatch in offer and demand on the labor market cause the precarity and limit the social mobility of this particular group of self-employed.

The second precarious career cluster shows an inverse trend by entering self-employment as a slightly delayed response to the global crisis in 2010/11 after a period of inactivity. This seems to be a rural and mostly female phenomenon. This group shows low levels of education and income. So, we might see women who are forced to work to support their families as a consequence of the crisis. This is in line with research showing higher female SE-rates in countries that do not provide high salaries, necessitating them to create a job for themselves and support their families (Pines et al. 2010). The rural setting implies fewer job opportunities than the urban labor market, so the main factor driving people into precarious self-employment might be a mismatch of skills and jobs. Finally, coming from a position of inactivity adds to the precarity of these self-employed and hinders their upward mobility. Further education and governmental support might be able to strengthen the position of these two precarious groups on the labor markets and give them a better possibility for social mobility.

### 5.1 Limitations

Addressing self-employment careers longitudinally importantly adds to our understanding of the heterogeneity among the self-employed and their success, geographical distribution and potentially regional economic effects of self-employment. At the same time, it introduces specific challenges to the analysis and interpretation of the results. Conceptually, the idea of post-self-employment success and explaining this from pre-self-employment characteristics becomes problematic as the career itself is part and parcel of success. It simultaneously describes the conditions for self-employment and the success derived from the steps, making causal relationships on experience and self-employment outcomes difficult to establish empirically.

A more practical limitation lies in the challenge to include variables that are known to be important to understand self-employment dynamics, such as sector information. Some sectors have a higher incidence of self-employment; e.g., physicians are more likely to be self-employed than teachers. Additionally, there may be sector-specific trends that influence self-employment careers, such as an increase in freelancing careers in construction and health services (Thörnquist 2015). Lastly, people may change sectors or cannot be sorted into one if they are unemployed or inactive. Thus, implementing a single sector operationalization into the longitudinal assessment is not straightforward. By failing to include the sector information in the main analysis, unfortunately, we neglect one source of self-employment heterogeneity.

A third limitation is the lack of educational information of the self-employed. For our timeframe, educational data were not available for the entire sample. Information is available most consistently for people with a higher education which reduces the number of cases and introduces bias in the analysis. Due to the requirements of the statistical analyses and the skewness in the education data available, it could not be used in the regression. Still, it would be interesting to see whether education has a significant impact on our SE career clusters. A similar issue applies to professional training or further education that people might have undergone between 2003 and

2018. Unfortunately, we were only able to observe one socio-economic status at a time, so that individuals following an education besides their main job cannot be identified. Future research might be able to find an impact of graduate or professional education on the career pattern.

Another limitation to our study is that the locational data are only measured at the end of the observed period, disregarding mobility throughout the measured years. Therefore, all we can conclude is where people with certain career trajectories end up at a set point of time. Previous research shows that location and career interact in two ways—people move to regions that offer many job opportunities to start or advance their career or people act as the drivers of regional growth in employment opportunities in their location on the grounds of their human capital (Tervo 2016). It seems likely that mobility patterns in the early stage of a self-employment career would be related to the career patterns the people follow. The intersection between residential mobility and career development of self-employed appears a promising next step in unraveling the geography of self-employment careers.

## 6 Conclusion

In summary, this study uncovers some of the heterogeneity among the self-employed. In an exploratory fashion, we find self-employment career patterns that vary by the number of transitions, self-employment tenure and income development over time. These career patterns are summarized in three archetypes of self-employment careers: (1) Stable self-employment careers. (2) Mixed self-employment careers which are characterized by alternating spells of self-employment and wage employment. (3) Precarious self-employment careers which combine unemployment and inactivity with self-employment. The characteristics associated with the career types differ importantly with precarious self-employment careers being most prominent among older people, women, and lower educated.

In terms of regional differences, we find that stable self-employment careers are more rural, while mixed and precarious careers are overrepresented in urban municipalities. This suggests a mediating effect of regional context on the development of self-employment careers.

In conclusion, this study reiterates the potential of conceptualizing self-employment in the context of careers rather than as a singular event. It strengthens the evidence for the three archetypal self-employment careers, adding the dimension of location and opens up research avenues that address the mechanisms behind the development of self-employment careers, also in relation to their regional context.

## Appendix

See Fig. 4.

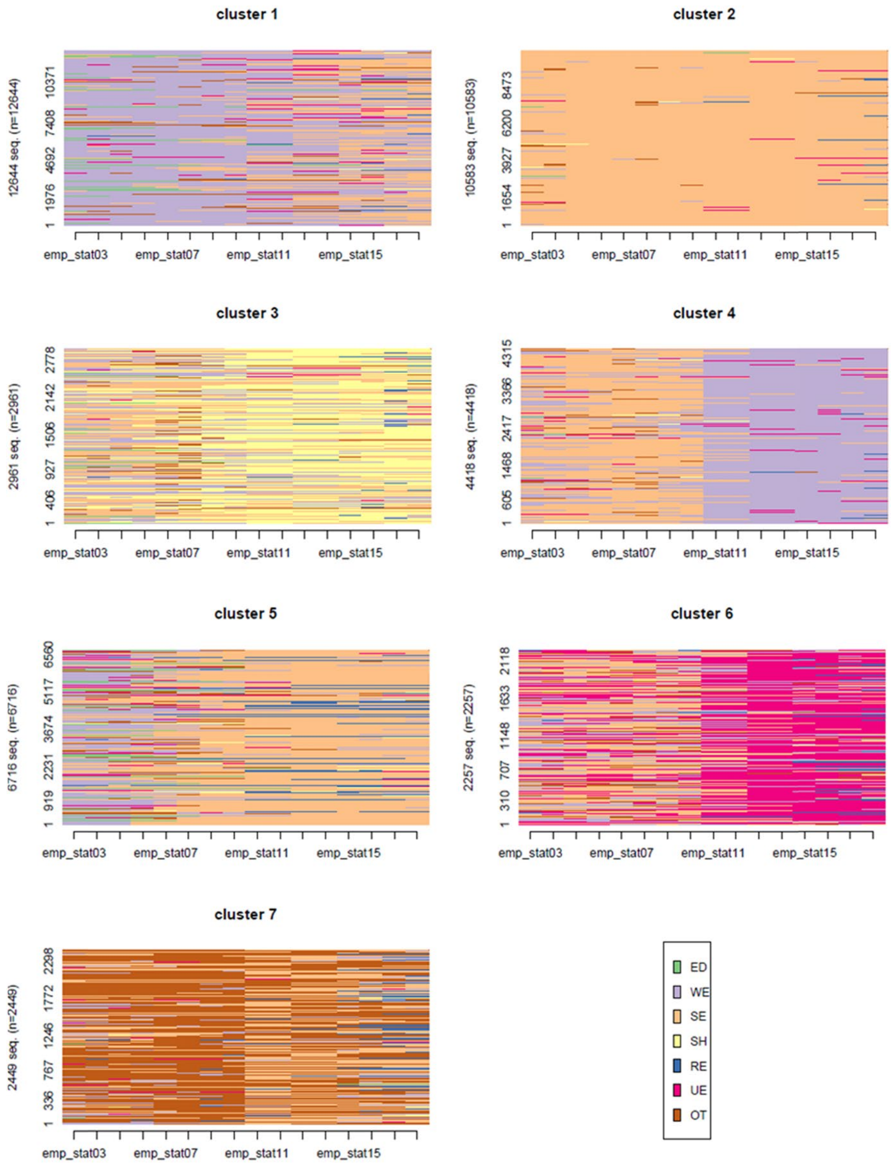


**Fig. 4** Sequence index plots of the career clusters, the horizontal axis plots the time 2003–2018, the vertical axis plots individual career sequences, each horizontal line describes one individual, the different SES are indicated by colors, total N per cluster is shown left of each graph

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**Code availability** Codes for R and SPSS available from researchers upon request.

## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.



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