Career Trajectories of Foreign-born Workers in Europe: a Retrospective Study Using SHARELIFE Data.

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Work in Progress

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ABSTRACT

In Europe, migration flows are often related to work reasons. For some countries with tight and/or aging labor markets and facing long-term hiring difficulties in specific sectors, recruiting foreign-born employees could be a promising solution in the coming years. However, improving the professional integration of these migrants remains a big challenge.

To better understand the mechanisms of this integration, we focus on the career trajectories of foreign-born workers based on the European survey SHARE. Thanks to the retrospective SHARELIFE component of this survey, it is possible to reconstruct professional careers year by year. We reach several interesting conclusions using the sequence analysis methodology and descriptive indicators suited to studying individual trajectories.

Our results confirm a greater complexity of migrant careers compared to natives. This complexity either takes the form of greater precarity (low-skilled or episodic employment) or results from more frequent upward transitions, especially for migrants from OECD countries. Thus, although migrant workers often experience overqualification for their first job, a form of catch-up seems possible. Finally, it should be noted that the careers of second-generation migrants (whose parents were both born abroad) no longer significantly differ from natives, which indicates successful long-term integration.

This paper uses data from the last release of SHARE and SHARELIFE surveys (waves 3, 7, and 8).

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1. INTRODUCTION

According to Eurostat figures, in 2020, 3.3 million people entered one of the EU member states, including 1.9 million from non-EU countries (Eurostat, 2022). Similarly, a recent OECD report (OECD, 2022) shows that, in OECD countries, foreign-born represent approximately 12% of the total population. This is roughly the same in the EU-27 member states. However, there are striking disparities between countries: in 2019, 47.5% of the population was foreign-born in Luxembourg, but less than 1% in Poland or Romania (Dorn & Zweimüller, 2021).

The phenomenon of migration is, therefore, far from negligible in Europe, whether intra-EU migration or non-EU migration. One of the fundamental reasons for these migrations is work. Migration is expected to have a beneficial effect in terms of career, income, and global life quality. Based on European data, Gruber and Sand (2022) show that, compared to people who stayed in their home country, the situation of migrants is generally better, and their expectations seem to be realized: subjective well-being, as well as income levels of migrants, are higher.

However, as Dorn and Zweimüller (2021) point out, much remains to be done to integrate migrants into European labor markets. Compared to natives, access to employment is more difficult for migrants; their wages are lower, not to mention the discrimination they experience. This is especially true for migrants from countries poorer than the destination country, as is often the case. Dorn and Zweimüller (2021) show that the wealthiest countries (per capita income above the EU average) have a higher proportion of immigrants and fewer emigrants. The opposite is true for countries below the average.

From an economic point of view, international migration is sometimes considered a solution to specific labor market shortages (OECD, 2022). Nevertheless, in reality, the employment rates of migrants are often lower compared to natives. Although the gap tends to decrease, it remains particularly significant for non-EU migrants. There is also an overqualification of migrants (mainly from outside the EU), which leads to efficiency losses (OECD, 2022).

Among foreign-born people, men are slightly overrepresented (about 55%), as well as young people (the median age is 30). Migrants would be more likely to move to countries with a significant diaspora of their nationality (Dorn & Zweimüller, 2021) and to major European capitals and big cities (OECD, 2022). The level of education of migrants seems to be increasing; Dorn and Zweimüller (2021) show that, between 2000 and 2015, the proportion of immigrants (entering the EU) with third-level education significantly increased.

To better understand the professional integration of migrants in European labor markets, we propose to study their career trajectories. This could allow better anticipation of a phenomenon expected to amplify in the coming years. Moreover, improving the inclusion of migrant workers also seems a promising way to address increasing hiring difficulties in many EU countries, especially for high-level jobs. Yet, as Gruber and Sand (2022) indicate, we know little about the post-migration life of these people who leave their countries. This is especially true for their professional careers.

The purpose of this article is to gain a better understanding of the professional trajectories of migrants. Do they have trajectories that look like those of natives? Are they overqualified? Once employed, are these trajectories relatively upward or rather downward?

In the following lines, the word immigrant refers to individuals born in a country other than their country of residence. When necessary, we will distinguish between first-generation immigrants (those born in another country) and second-generation immigrants (whose both parents were born abroad). Among first-generation immigrants, we have chosen to distinguish those coming from an OECD country from others.

1.1. Professional career

Arthur and Rousseau (1996, p. 30) define a career as *“the unfolding sequence of any person's work experiences over time.”* Thus, a professional career has a sequential and longitudinal dimension that must be considered. An individual's career is based on individual choices, organizational mechanisms (HR policies), and contextual factors. The policies implemented in the country, as well as the economic situation, can have an impact on these careers. Individual decisions are obviously *“socially embedded,”* as Higgins (2011, p. 612) states.

Arthur and Rousseau (1996) propose the notion of *“boundaryless careers”* or *“protean careers”* to emphasize the fact that professional careers are no longer confined to a given organization but tend to become more complex according to arising opportunities. Biemann et al. (2011) explore this complexity in light of globalization and industrial growth in Germany. For them, the complexity of careers is probably overestimated.

Similarly, Kovalenko and Mortelmans (2014) are more measured about the extent of these boundaryless careers. They call *“traditional careers”* the dominant careers in the 20th century, which mark an individual's evolution within a company’s hierarchy, a company to which they generally remain loyal. In doing so, they reap the benefits of their internal progression (compensation, responsibility, status). There are few external mobilities. These traditional careers are at odds with *“transitional careers”* (boundaryless or protean) based on mobility. As their name suggests, they involve many transitions between companies or sectors. For Kovalenko and Mortelmans (2014), these two perspectives on careers coexist and accurately describe diverse realities. Interestingly, they also indicate that some workers can perceive so-called transitional careers as unstable and precarious. The coexistence of these two types of careers is confirmed by Häfeli et al. (2021). In the Swiss context, stable and linear careers are more common among women, while men tend to have more mobility-based careers with upward trajectories.

1.2 Careers and migration

A quite widespread idea in the literature on migration is that the professional mobility of migrants displays a U-shape pattern (Fellini & Guetto, 2021). Thus, upon their arrival in the country, immigrants would experience a downward phase (less pronounced for individuals with easily transferable skills), accepting jobs at a lower level than their level of education or the position they previously held. Then, over time, there would be a form of catch-up to return to their initial level. While this may be true in deregulated markets, Fellini and Guetto (2021) do not find these U-shaped careers in regulated and segmented labor markets such as the French, Italian, or Spanish markets. The downward phase would be more long-lasting, and the chances of catch-up lower as market segmentation increases.

Kogan (2007), using a methodology comparable to ours on German data, shows that the careers of immigrants from European countries are relatively similar to those of native Germans. Similarly, second-generation immigrants and younger generations of Germans have similar career patterns, suggesting successful integration into the labor market. In contrast, immigrants from Turkey or former Yugoslavia, for example, have notable trajectory differences with natives, often marked by periods of unemployment and low-skilled jobs.

Finally, Shroot (2022), using 30 interviews with Romanian, German, and Italian migrants, gives some insights into the reasons for migration. Professional expectations are certainly one aspect (gaining experience, upskilling), but not the only one. Some migrants are looking for a different lifestyle, sometimes fleeing an unsatisfactory socio-political context or migrating for family reunification and a better quality of life for their children. When the motive for migration is professional, Schroot (2022) emphasizes the existence of two predominant trajectories, one horizontal with a transfer of skills in a similar activity. The other, vertical, requires integration into a different activity, often at a lower level, and implies acquiring new skills.

2. METHODOLOGY

2.1. Data presentation

This paper uses data from the "Survey of Health, Ageing, and Retirement in Europe" (SHARE), including its retrospective component SHARELIFE[1], and the Job Episodes Panel generated from waves 3 and 7 of the SHARE survey. Börsch-Supan et al. (2013) provide methodological details on the SHARE survey, while Brugiavini et al. (2019) describe the Job Episodes Panel. SHARE is an eight-wave survey targeting people over 50 years. During waves 3 and 7, a retrospective component (SHARELIFE) was addressed to individuals from the regular survey. In this specific questionnaire, respondents were asked to trace their significant life events using a life history calendar technique.

We study the professional career, defined as a given person's job sequence. These retrospective elements are complemented by recent elements from the regular survey collected during the last wave (wave 8 in 2019/2020), particularly for the latest stages of individuals' professional life and demographic variables. Thus, our population consists of individuals from wave 7 (SHARELIFE) who also responded to the last wave of the regular survey (wave 8 of SHARE). This represents 41,359 individuals.

However, several other choices were made, which reduced this population to 9103 individuals.

- We kept individuals who retired between 2000 and 2020, allowing us to work on entire careers. These people were born between 1933 and 1960 (some outliers were deleted).
- A career is composed of 52 successive states corresponding to 52 years of follow-up from the 15^{th} year of age to the 67^{th} year. Individuals with more than 26 missing values throughout their careers were excluded. However, 96% of the population studied has less than ten missing values.
- Only people with work sequences identified by a 4-digit ISCO-08[2] code (which was not the case in wave 3 of the survey) were selected. This offers a finer granularity in the analysis of skill levels (see below).

Indeed, each work sequence is identified either by the ISCO-08 code of the job held (as Häfeli 2021 also does) or by a code indicating that the individual was not employed, regardless of the reason. A more detailed codification of non-employment situations would be possible, but we focus on professional careers in this paper.

A significant benefit of the ISCO classification is the ability to map ISCO codes with the job's required skill level (ILO, 2012). This allows grouping ISCO codes according to skill levels:

- Skill level 4: Managers and Professionals (major groups 1 and 2)[3];
- Skill level 3: Technicians and Associate Professionals (major group 3);
- Skill level 2: Operators, clerical workers, skilled workers (major groups 4 to 8)
- Skill level 1: Elementary occupations (major group 9).

[1] Waves 3 (DOI: 10.6103/SHARE.w3.800), 7 (DOI: 10.6103/SHARE.w7.800) and 8 (10.6103/SHARE.w8.800).
[2] International Standard Classification of Occupations, 2008 version.
[3] As described in ILO (2022), sub-major group 14 was placed in skill level 3.

We thus obtain five possible states: four skill levels and a non-employment state.

Table 1. Descriptive statistics

	Female (N = 4,610)	**Male (N = 4,493)**	**Overall (N = 9,103)**
Percent of gender (weighted)	51% (47%)	49% (53%)	100%
Average age of respondents (weighted)	71.6 y. (71.6)	72.5 y. (71.1)	72.1 y. (71.3)
Education Level (weighted %):			
High	1,109 (23%)	1,154 (28%)	2,263 (26%)
Medium	1,266 (30%)	1,199 (30%)	2,465 (30%)
Low	2,216 (47%)	2,130 (42%)	4,346 (44%)
Missing	19	10	29
Migratory Status (weighted %):			
First-generation, non-OECD	220 (2.9%)	184 (2.3%)	404 (2.6%)
First-generation, OECD	110 (2.5%)	124 (2.2%)	234 (2.3%)
Second-generation	259 (4.2%)	205 (3.4%)	464 (3.8%)
Native	4,003 (90%)	3,956 (92%)	7,959 (91%)
Missing	18	24	42

Throughout the paper, we use the sampling design proposed by the SHARE team (individual calibrated weights and stratification) to ensure better representativity of our results. For example, respondents come from 26 different countries (presented in Annex A). Therefore, using calibrated weights to respect the relative population size of these countries is essential. Note that three countries are missing: the Netherlands (due to a mixed-mode experiment in wave 7), Portugal (no participation in main wave 8 due to COVID), and Ireland (no participation in wave 7).

2.2. Sequence analysis tools

Dlouhy and Biemann (2015) provide a list of articles using sequence analysis (in particular Optimal Matching) to analyze career trajectories. However, few articles, except Kogan (2007) mentioned earlier, use this technique to study migrants' careers.

The strength of sequence analysis, which we will use in this paper, is to exploit the longitudinal dimension of careers and study *"sequences of occupational states as wholes"* (Dlouhy & Biemann, 2015, p. 63). The aim is to highlight similarities between individual trajectories, allowing to regroup individuals into meaningful clusters (based on their proximity). Then it is possible to link these clusters with other explanatory variables to understand their composition better. This methodology has been used in many contexts, e.g., epidemiology (Larmarange et al., 2015) or even DNA sequencing. It was further developed by a team at the University of Geneva, proposing an analysis tool, the TraMineR package of the R software (Gabadinho et al., 2011), which we extensively used.

We consider the trajectory of an individual as a "sequence" characterized by a succession of states. As mentioned earlier, five states are possible in our analysis. They form the so-called "alphabet" of the sequence. Each sequence can then be treated as a list (ordered in time) of the states visited by an individual. Table 2 shows two examples of individual sequences over ten years of observation.

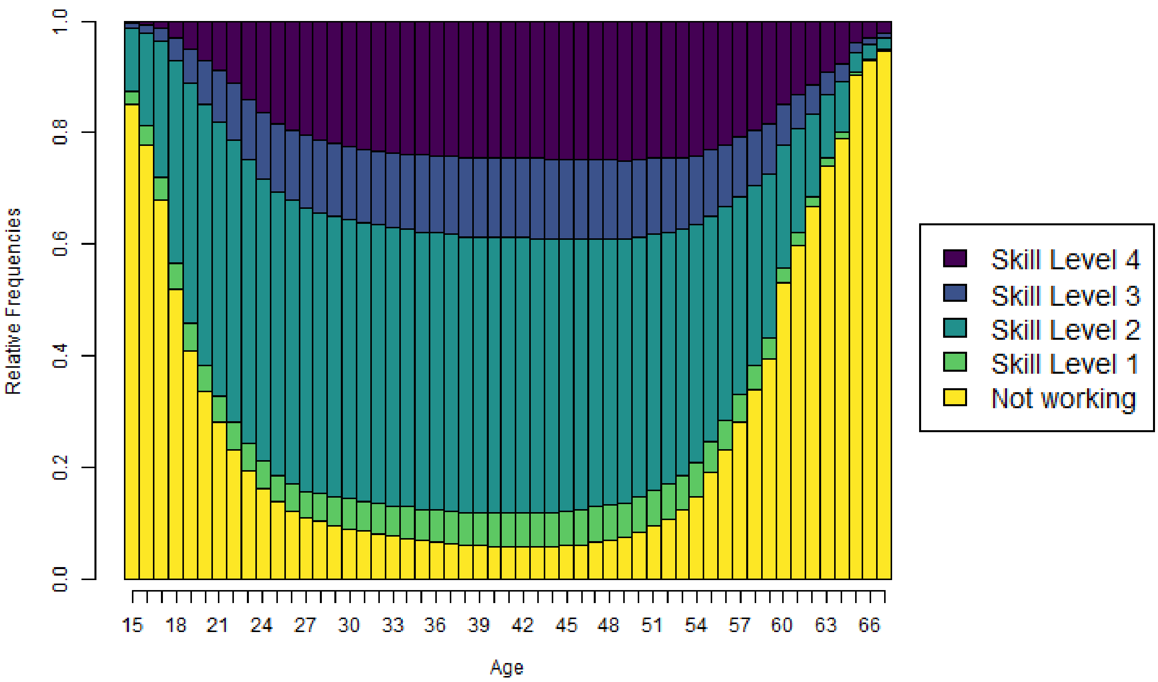
Table 2. Individual sequences examples

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Indiv. #1	NW	L4	L4	L4	L4	L4	L4	L4	NW	NW
Indiv. #2	NW	L3	L3	L3	L4	L4	L4	L4	NW	NW

The first individual has a straight career trajectory, remaining permanently at the fourth qualification (L4). His career comprises ten successive states and three spells: a non-working spell (NW), a spell at level 4 lasting seven years, and another non-working spell corresponding to retirement. Individual #1 also experiences two transitions, one from NW to L4 and another from L4 to NW. The second individual (#2) has a similar career trajectory, but with an additional transition (and therefore four spells) since, from year 5, he moves to job level 4.

The states of the entire population are commonly represented using a state distribution plot (also called a chronogram, see Figure 1), which shows the distribution of states for each year of observation[4]. Another representation commonly used in sequence analysis is the sequence index plot, where all individual sequences are superimposed in a single graph (an example is provided in Annex C for the clusters used in this paper).

Figure 1. State distribution plot (chronogram)



Now, the critical point is how to group individuals with similar careers, in other words, according to the degree of similarity in their sequences. This is precisely what the Optimal Matching method allows us to do. The idea is to compare sequences pairwise and to determine which modifications would be necessary to "transform" one sequence into another existing sequence. These modifications are expressed as a cost. Two types of costs exist:

- a so-called "indel" cost (for insertion, deletion), which is the cost of an insertion or a deletion of a state in the sequence;
- a substitution cost, i.e., the cost of replacing one state with another state.

[4] For example, at 42 years, 5.6% of the studied population does not work; 6% hold a first-level job; 48.7% a second-level job; 14.2% a third-level job; and 24.2% a fourth-level job. There are 1.3% of missing values.

If the indel cost is set to 1, it makes sense to put the substitution cost to 2 since substituting a state for another is equivalent to deleting a state and inserting another one. For example, in the two individual sequences presented above (Table 2), three substitutions would be required to transform sequence #2 in sequence #1 (states of years 2, 3, and 4), resulting in a cost of 6. The lowest modification cost is chosen if there are different ways to transform the sequence.

In our paper, we slightly modify these costs to consider that the modification costs are not identical in all transitions. For example, it is, in some ways, more "expensive" to move from level 2 to level 4 than from level 2 to level 3. This is achieved by weighting the costs by the transition probabilities between the different states.

Then, the costs required to move from each sequence to each of the other sequences are calculated. Obviously, the lower this cost, the closer the two sequences are. In practice, this means generating a distance matrix (or dissimilarity matrix) containing the distance metrics (costs) between individual sequences. This is a square matrix (dimension 9103 x 9103 here).

Finally, we perform a hierarchical clustering based on Ward's distance[5] to group the trajectories into clusters.

2.3. Individual sequences indicators

In addition to the tools allowing the implementation of Optimal Matching, the TraMineR package provides valuable indicators for studying the nature of individual sequences (Ritschard, 2021). We will use several of them. Some are straightforward:

- the average duration of a spell: how long does a person stay in a similar state?
- the number of transitions in the sequence, i.e., state changes throughout the career.

Other indicators are more refined. For example, Gabadinho et al. (2010) propose a complexity index. This composite indicator measures both the number of transitions and the time spent in each state through a calculation of entropy (i.e., a measure of the heterogeneity of a sequence: the more diverse the states an individual goes through, the higher the entropy will be). The complexity index $C(s)$ is then defined as the geometric mean of the longitudinal entropy $h(s)$ and the number of transitions $nt(s)$; both terms are normalized:

$$C(s) = \sqrt{\frac{nt(s)}{l(s)-1}\ \frac{h(s)}{h_{max}}}$$

where h_{max} is the maximal entropy and $l(s)$ the length of the sequence. Thus, $l(s)-1$ represents the maximal number of transitions.

Ritschard (2021) also proposes a degradation index that is particularly useful to detect upward and downward trajectories. This simply involves subtracting the proportion of upward transitions $q^{+}(s)$ in the sequence from the proportion of downward transitions $q^{-}(s)$:

$$D(s) = q^{-}(s) - q^{+}(s)$$

Since some transitions involve "skipping" multiple levels, these proportions are weighted.

[5] Other methods were tested, such as the UPGMA method (Unweighted Pair Group Method with Arithmetic mean) and beta-flexible UPGMA, without substantial improvement.

3. RESULTS

3.1. Clustering results

After implementing the above-presented methodology, we obtain two possible partitionings: into 5 or 8 clusters. Although the quality statistics favor a 5-class partitioning[6], opting for a division into eight classes seemed more relevant to distinguish between stable and more chaotic trajectories. Indeed, we hypothesize that migrant workers have less stable careers than natives. This is why keeping classes containing more chaotic paths makes sense and opens up a finer understanding of professional trajectories. As we can see in the sequence index plots (Annex C), this is the case in the 8-class option.

Here is a brief description of these eight classes. The chronograms and sequence index plots provided in Annex (B and C) show which kinds of careers are included in the different classes. For more clarity, we choose to present these classes in four pairs: managers and executives (clusters 1 and 8), technicians (2 and 6), workers (4 and 5), and precarious classes (3 and 7).

Class 1: Stable managers (n=1691)
Class 1 mainly comprises managers and executives (skill level 4) with steady careers. Some upward transitions (spells in level 3) exist, but stability remains the standard. The study period is more extended than in other classes. High variability in the retirement age can be observed, with sometimes very early retirements.

> *Class 8: Unstable managers (n=832)*
> Class 8 relates to class 1; the composition is roughly the same, but more chaotic careers are observed, with more upward and downward transitions and even unemployment spells. These individuals have spent less time at skill level 4 and have experienced various situations. The average spell duration is also higher (see Table 3).

Class 6: Stable technicians (n=861)
Class 6 is mainly composed of technicians (skill level 3) with remarkably stable careers. The education period is shorter than for managers, and the retirement age is more uniform (around 60 years). Some ascending and descending trajectories exist, but people in this class generally spend most of their careers at skill level 3.

> *Class 2: Ascending technicians (n=510)*
> Technicians from class 2 first went through blue-collar jobs (skill level 2) and then progressed to level 3. Numerous ascending transitions from level 2 to level 3 (with various durations in these states) are observed. There are some atypical careers, with non-working periods or (rare) upward changes to skill level 4.

Classes 4 (n=1550) and 5 (n=2616): Stable workers
These two classes are very similar and form the core of our population: the distinction between these classes 4 and 5 is less significant than in the other cases. They pool workers (clerical, craft, sales, and operators) who remain at skill level 2 for a long time, usually throughout their careers. In class 4, transitions are infrequent, and sequence complexity is very low (see Table 3). Class 4 comprises people who have completed short studies or started working very young and directly entered a second-level job, where they remained until retirement (typically around 60 years). Class 5 resembles class 4, including people with slightly longer studies and/or earlier retirements. Men are largely overrepresented in class 4.

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[6] The value of a widespread quality indicator, the (weighted) Average Silhouette Width, is 0.547 for the 5-class partitioning and only 0.272 for the 8-class partitioning. Ideally, it should be above 0.5.

Class 3: Elementary professions (n=579)

Class 3 includes people who remained in an elementary profession (skill level 1) for a long time or experienced a downward transition (from level 2 to level 1). This class has much more precarity, with generally low education levels. Women are overrepresented in this category, and even more in class 7.

Class 7: Episodic working or non-working (n=464)

This last class includes people who never worked for various reasons, including homemakers and sick people, but also people who worked episodically, mainly at level 2. These individuals often remained in the same state for a very long time (26.8 years on average, see table 3) and probably experienced precarity and unemployment.

Table 3. Clusters description

	% female	**% low Educ.**	**% high Educ.**	**Mean spell duration**[1]	**Mean nb. of transitions**[1]	**Complexity Index**[1]
Class 1	51.4%	6.3%	**71.7%**	15.7 (3.6)	2.52 (1.03)	0.13 (0.04)
Class 2	49.2%	30.9%	15.4%	**11.2** (3.0)	**3.98** (1.49)	**0.21** (0.05)
Class 3	**57.0%**	**60.5%**	1.6%	14.3 (5.5)	3.15 (1.58)	0.16 (0.06)
Class 4	28.3%	41.1%	8.6%	18.6 (6.5)	**2.10** (1.11)	**0.09** (0.04)
Class 5	45.7%	31.5%	13.1%	14.5 (4.2)	2.86 (1.45)	0.15 (0.05)
Class 6	39.8%	15.9%	32.8%	14.9 (4.3)	2.74 (1.21)	0.14 (0.05)
Class 7	**83.0%**	**61.8%**	8.4%	**26.8** (19.2)	2.43 (2.44)	0.11 (0.10)
Class 8	48.4%	9.8%	**48.2%**	**10.7** (3.1)	**4.18** (1.48)	**0.22** (0.05)
Overall	46.5%	30.0%	25.6%	15.9 (7.7)	2.79 (1.53)	0.14 (0.06)

[1] Standard deviation in brackets. Wilcoxon rank-sum test for complex survey samples: $p < 0,001$

Table 3 gives complementary indications on gender and education levels. Three additional indicators draw attention to some classes. Thus, clusters 2 (ascending technicians) and 8 (unstable executives) are characterized by lower spell durations and increased transitions. Furthermore, the complexity index indicates that these classes have less linear trajectories than, for example, classes 1 (stable executives) and 6 (stable technicians).

Similarly, class 4 stands out because of very steady and non-complex careers. Therefore, in the next step, we will use this class as the reference for the multinomial logistic regression.

3.2. Multinomial logistic regression

To evaluate in which classes migrant workers are more likely to fall in, we use a multinomial logistic regression. This multivariate approach allows us to use other variables as control variables and to study migratory status, all things being equal. To fine-tune the model and check its robustness, we also used a bootstrap method, which confirms the stability of the coefficients and p-values.

For more simplicity, the odds ratios of the model (i.e., exponentiated regression coefficients) are shown in Table 4. As a reminder, an odds ratio equal to 1 indicates no effect, an odds ratio greater than 1 indicates higher chances compared to the reference (conversely, an odds ratio less than 1 indicates lower chances). For example, the odds of being in class 3 (rather than in class 4, which is the reference) are much higher (3.458 times higher) for first-generation migrants from non-OECD countries than for natives.

Table 4. Odd-ratios (class 4 is reference)

Estimates:	Class 1	Class 2	Class 3	Class 5	Class 6	Class 7	Class 8
Intercept	0,238***	0,219***	0,173***	1,359*	0,382***	0,038***	0,271***
Gender:							
Male (ref.)	–	–	–	–	–	–	–
Female	3,414***	1,988**	2,997***	2,055***	1,915***	15,1***	2,509***
Children:							
No children	0,884	0,227**	1,032	0,899	0,905	4,042*	0,714
One or two children (ref.)	–	–	–	–	–	–	–
More than two children	1,030	0,546*	0,918	1,013	1,276	1,309	0,956
Female with:							
No children	1,381	5,041*	0,568	1,137	0,869	0,211	1,308
One or two children (ref.)	–	–	–	–	–	–	–
More than two children	1,005	1,578	1,666	1,172	0,806	1,627	1,181
Education:							
High	22,2***	1,842*	0,290**	1,539	4,106***	2,221*	7,649***
Medium (ref.)	–	–	–	–	–	–	–
Low	0,374***	0,789	2,120***	0,742*	0,397***	2,667***	0,310***
Generation:							
1933-1945	0,870	0,849	0,668	0,623***	0,680*	0,792	0,755
1946-1950 (ref.)	–	–	–	–	–	–	–
1951-1960	0,791	0,886	0,823	1,055	0,852	0,730	0,801
Migratory Status:							
First-gen., non-OECD	2,132	1,557	**3,458***	1,660	2,334	**2,897***	**3,430***
First-gen., OECD	1,091	0,960	0,689	0,636	1,037	0,514	1,300
Second-gen.	0,793	1,185	1,064	0,813	1,339	0,568	1,366
Native (ref.)	–	–	–	–	–	–	–

Demographic variables

Here, demographic variables are used mainly as control variables. However, we can quickly review them as they confirm what has been said earlier.

Gender and age, first. Women are more likely to be in all categories rather than in the reference class (class 4 of stable workers). This is explained by the fact that the reference class is very male-dominated. The odds of female respondents being in class 7 are particularly high. This class includes homemakers or those who experienced very short and disparate work episodes. The birth generation has little effect on the results. The only two significant odds ratios indicate that individuals born between 1933 and 1945 are likelier to fall into the "stable workers" class.

Family responsibilities do not seem to have a significant effect, neither for women nor for men. There seems to be a predominance of men without children in class 7 (episodic work) and women without children in class 2 (ascending technicians). This could be explained by the fact that women without children can devote more time to their career development.

Education levels show a strong influence. This can partly be explained by the fact that in the ISCO classification, skill levels (used to characterize individual sequences) are related to the ISCED[7] classification used for education levels. However, the results are not surprising, as the managers' (1 and 8) and technicians' classes (2 and 6) require a higher education level than the reference class, in contrast with classes 3 (elementary professions) and 7 (episodic work).

[7] International Standard Classification of Education.

Migratory status

The lack of effect for second-generation migrants (those whose both parents were born abroad) is a first interesting result. The model does not highlight any significant difference between this category of individuals and native workers. This indicates a successful professional integration of second-generation immigrants and confirms results from other studies, such as Kogan's (2007). More surprisingly, this seems also to be the case for first-generation immigrants from OECD countries. As we will see below, finer indicators are required to emphasize specificities for these.

This regression confirms a specific distribution of migrants from non-OECD countries in our eight clusters. They are more likely to fall into unstable and complex classes. Thus, compared to class 4 (stable workers), these individuals have more chances to be:

- in class 3 (elementary professions) and class 7 (episodic work), which seems to confirm that some migrants from non-OECD countries move toward less qualified jobs and experience more precarious trajectories than natives;
- in class 8 (unstable executives): this tends to confirm the existence of another category of migrants with higher levels of qualification and upward trajectories. Here, one would instead expect migrants from OECD countries, but the result is not significant for them.

Odds ratios are known to overestimate the effects slightly. So, we could also take some specific examples to compare non-OECD migrants to natives. For example, let us take the following situation:

A man without children, born between 1946 and 1950, with a low level of education.

For this person, we could calculate the probability of being in class 3[8]: 55.9% compared to 26.8% for a native, i.e., a two-times higher probability (2.1 times). For classes 7 and 8, this individual has respectively 2.5- and 2.9 times higher probabilities than natives. Note that this result is true in the specific situation we described.

Now we change one (and only one) factor in this situation: education level. We notice that the difference between first-generation non-OECD migrants and natives is also very high for classes 3 and 7 but reduces for class 8: a non-OECD migrant has only a 30% higher probability than a native worker. This could be the sign that, as the level of education increases, the gap between natives and immigrants is closing. The same is true when considering women.

These results, interesting in themselves, nevertheless lead us to explore more deeply the nature of individual sequences of migrants.

3.3. Further analysis

Upward and downward career transitions

Sequence analysis and clustering do not fully account for upward and downward career transitions. To do this, it is possible to calculate a degradation index (see section 2.3) for each individual sequence. When this index equals 0, there is no transition in the sequence. The predominance of downward trajectories is reflected by positive values of the degradation index (values between 0 and 1), while upward trajectories are characterized by negative values (between 0 and -1). We built a categorical variable from this index that is crossed with migratory status in Table 5.

[8] Versus class 4, as indicated several times above.

Table 5. Upward and downward transitions of migrants

	% Stable	% Downward	% Upward
Migratory Status:			
First-generation, non-OECD	61.9%	**15.9%**	**22.3%**
First-generation, OECD	45.6%	**14.8%**	**39.6%**
Second-generation	71.2%	12.8%	16.0%
Native	69.4%	12.2%	18.3%
Overall	68.7%	12.4%	18.9%

Chi² with Rao & Scott adjustment: $p < 0.001$

The most striking observation is that migrants have more upward trajectories than natives. This is especially true for migrants from OECD countries. Second-generation migrants' trajectories are very close to those of natives. Downward trajectories are slightly more frequent among migrants, especially those from non-OECD countries.

Table 6. Cross-sector transitions of migrants

	Industry to Services		Services to Industry	
	No transition	**Transition(s)**	**No transition**	**Transition(s)**
Migratory Status:				
First-generation, non-OECD	77.6	**22.4**	91.0	9.0
First-generation, OECD	78.8	**21.2**	84.1	15.9
Second-generation	85.2	14.8	89.8	10.2
Native	86.1	13.9	91.8	8.2
Overall	85.6	14.4	91.5	8.5

Chi² with Rao & Scott adjustment: $p = 0.062$ (Ind. to Serv.) and $p = 0.065$ (Serv. to Ind.)

We can further refine the analysis by looking if these transitions occur within the same economic sector. In the overall population studied, cross-sector transitions occur most frequently (in 69% of all cross-sector transitions) between the services and industry sectors. It seems that transitions from industry to service are slightly more frequent for migrants than for natives, but the result is not entirely significant.

Overqualification

Finally, sequence analysis does not allow for measuring the potential overqualification of migrant workers. By overqualification, we mean individuals with educational attainment above the requirements of their first job. It is a widely accepted idea in the literature that migrants (particularly from poorer countries) tend to accept jobs with lower skill levels.

Table 7. Overqualification and underqualification of migrants (first job)

	Equivalent qualification	Overqualified	Underqualified
Migratory Status:			
First-generation, non-OECD	45.9	**25.4**	28.8
First-generation, OECD	49.3	**30.7**	20.0
Second-generation	59.3	12.0	28.8
Native	57.0	16.6	26.4
Overall	56.6	16.9	26.4

Chi² with Rao & Scott adjustment: $p = 0.003$

As shown in Table 7, overqualification is frequent among first-generation migrant workers and even more among migrants from OECD countries. However, according to the literature on U-shaped careers, this overqualification in the first job may be resolved later. The frequency of upward career trajectories among migrants (see the previous point) could be a sign of this catch-up over time.

4. CONCLUSION

Our study still needs to be deepened. Among possible avenues for improvement, we would like to consider the destination country's specificities since economic and social policies are supposed to influence careers. In addition, the 638 sequences of first-generation immigrants could be analyzed separately to detect specific patterns that may remain unnoticed in a comparison with native workers. It could also be interesting to compare with their pre-migratory trajectories or to seek the signs of U-shaped careers more precisely, as emphasized in the literature. In parallel with fine-tuning the multinomial logistic regression, we must investigate these areas to improve this article.

However, interesting findings can be drawn from our work. Here, as a summary, are the three most important ones. First, we show that migrant workers' career trajectories are generally more unstable and complex than those of native workers. Professional transitions more often mark their careers. However, second-generation immigrants do not show significant differences from natives anymore: time seems to be on the side of the professional integration of migrants.

Second, we confirm the existence of two types of career trajectories among migrants, validating, for example, the work of Schroot (2022). For some immigrant workers, the frequency of transitions reflects a form of precarity. These individuals, often from non-OECD countries, accept low-skilled jobs or work only episodically. On the other hand, another category of migrants, with a higher level of qualification and coming more likely from OECD countries, integrate highly skilled jobs or have ascending trajectories allowing them to access such jobs after some years.

Third, while a clear overqualification of immigrant workers can be observed when they enter their first job, the frequency of ascending trajectories suggests a form of catch-up in the following years. This confirms a U-shaped career pattern and is a promising avenue that we need to explore further.

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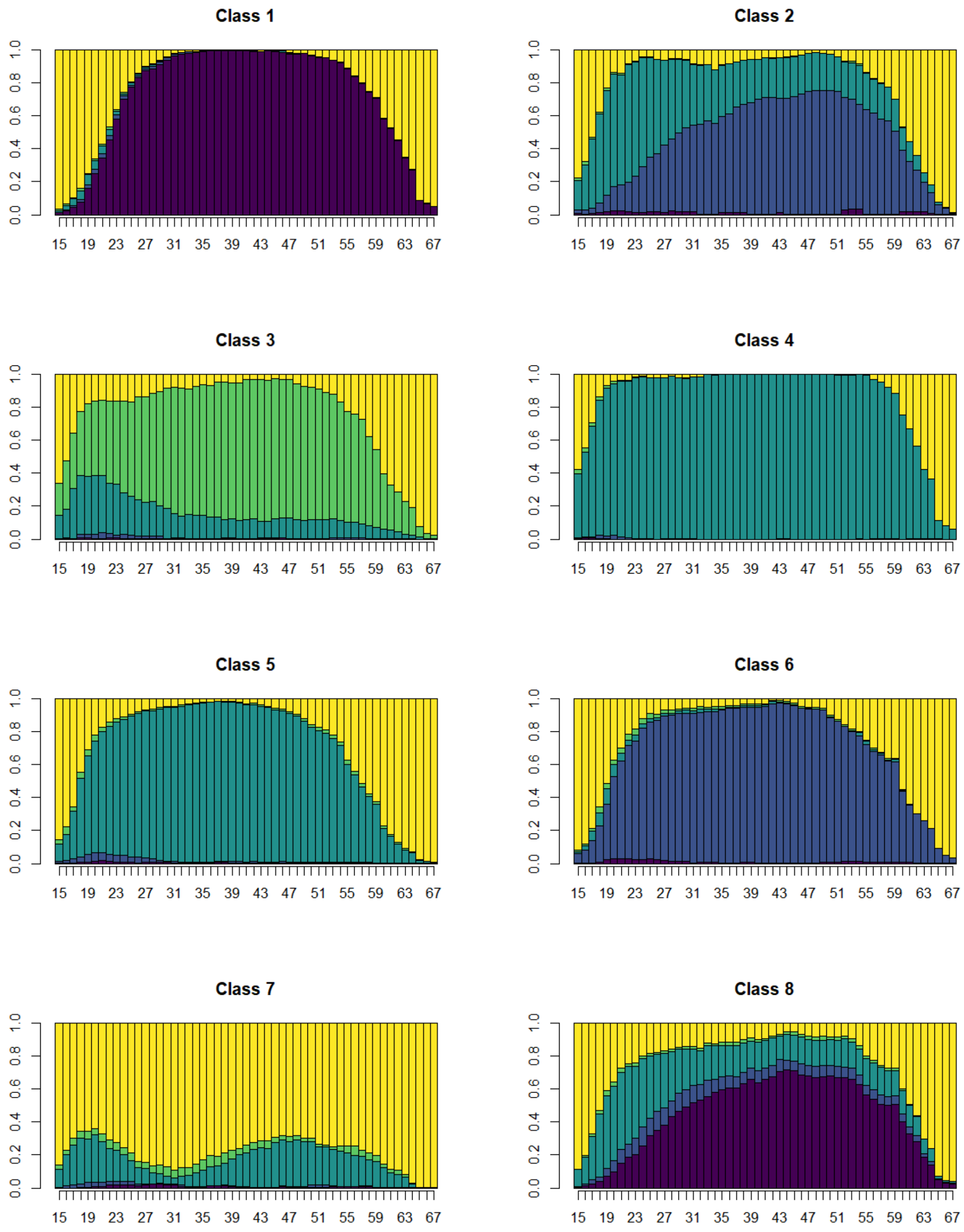
Annex A. Respondents' countries

	Country (N = 9,103)	**Relative frequency**	**With survey weights**
Austria	491	5.4%	3.8%
Belgium	344	3.8%	2.5%
Bulgaria	230	2.5%	2.7%
Croatia	383	4.2%	1.9%
Cyprus	74	0.8%	0.1%
Czech Republic	956	10.5%	4.2%
Denmark	233	2.6%	0.8%
Estonia	822	9.0%	0.5%
Finland	148	1.6%	1.1%
France	377	4.1%	14%
Germany	688	7.6%	26%
Greece	160	1.8%	1.2%
Hungary	105	1.2%	1.2%
Israel	267	2.9%	2.1%
Italy	257	2.8%	10%
Latvia	69	0.8%	0.3%
Lithuania	124	1.4%	0.4%
Luxembourg	265	2.9%	0.2%
Malta	86	0.9%	<0.1%
Poland	299	3.3%	6.6%
Romania	160	1.8%	3.2%
Slovakia	274	3.0%	2.0%
Slovenia	799	8.8%	0.9%
Spain	421	4.6%	9.3%
Sweden	698	7.7%	3.1%
Switzerland	373	4.1%	1.8%

Annex B. State distribution plots (chronograms) of clusters



Annex C. Sequence index plots of clusters