A life course perspective of personality traits and fertility

(DRAFT, please do not quote)

Abstract

This study argues that the established link between personality traits and fertility can be fruitfully investigated adopting a life course perspective. Contrary to earlier studies, we show that personality traits matter for life course trajectories, of which fertility is one outcome together with several others – the most important ones being individuals' union formation (and dissolution) and work careers. Using data from the German Socio Economic Panel we build sequence-types representations of the three careers, based on the events and activities undertaken between the ages of 20 and 40. We apply joint Sequence Analysis to identify clusters of individuals who experienced similar careers in the three domains, and then relate clusters to personality traits – controlling for a set of socio-demographic characteristics – via multinomial logistic regression. Since the number of cases with complete sequences is limited, we develop a new procedure to apply Sequence Analysis to trajectories of different lengths. This allows the analyst to incorporate individuals whose trajectories were observed only for a certain age span. Results show that personality traits shape significantly some life course trajectories more for men than for women, and with Consciousness emerging as the most important trait, bringing success in the job market and also in reproductive life.

1. Introduction

There is now an emerging literature demonstrating that personality traits (PTs) are linked to fertility behavior (e.g., Jokela 2012, Skirbekk and Blekesaune 2013, Tavares 2016). But there is also a literature linking personality with both union formation and union stability (e.g., Hewitt et al 2006; Lundberg 2012). Yet, at the same time, there is an abundant literature showing important connections between personality and job careers (e.g., Siebert and Kraimer 2001; Judge at al. 2006, White at al 2019). Fertility is often considered as a function of both union formation and career choices. Whereas this is not necessarily appropriate (many will make their fertility planning conditional on job and union dynamics), it is clear that for most people these processes evolve together, and that decisions in one domain are interconnected with events in the others. This paper tackles this issue head on by studying to what extent which PTs matter for individuals' life course trajectories. In other words, instead of investigating whether personality matters for specific events, we show that it matters for life biographies more broadly, whereby differences in fertility, job activities and union dynamics are part of those life course trajectories.

To this aim, we use data from the German Socio-Economic Panel survey (SOEP), a representative ongoing longitudinal study started in 1984, and include all the waves up to 2015. The SOEP collects the classical “Big Five” personality inventory, broadly accepted as consistent and reliable categorization of peoples’ psychological attributes (Goldberg 1981).

Methodologically, we employ what is known as Multichannel Sequence Analysis to study the joint evolution of the three key domains, namely family formation (and dissolution), childbearing and job career. Using cluster analysis, we identify groups of individuals who experienced similar trajectories on the three domains. We subsequently relate cluster membership to PTs via multinomial logistic regression, controlling for a set of additional socio-demographic covariates. Since only few surveyed people in our dataset were observed for the entire period of interest – namely between the age of 20 and 40 – we develop a novel approach to apply Sequence Analysis to trajectories of different lengths, i.e. possibly truncated or censored to the right. Thus allows including in the analysis also individuals whose trajectories were observed only for a limited age span, specifically and conveniently younger cohorts.

2. Personality Traits and fertility, union and job careers: a literature review

Several studies suggested that personality matters for childbearing. The existing empirical evidence on the relationship between PTs and fertility is principally achieved at the individual level and it provides contrasting findings, both because different measures of personality are employed, and because studies are performed across different socio-demographic contexts.

Whilst the relationship between the number of children and PTs may be studied taking an evolutionary perspective, thus aiming at investigating whether personality is associated with key life-history traits (see e.g., Alvergne et al., 2010), most of the existing studies relate to controlled fertility populations, where childbearing is very much a choice, and can be controlled through contraception. One of the first studies along this direction was conducted by Eaves et al. (1990) using Australian data. They find higher completed fertility among women who score high on “Extraversion” and score low on “Neuroticism” (although with completed fertility higher than the average for the opposite combination of low “Extraversion” and high “Neuroticism” scores). Miller (1992) investigates childbearing motivations using the 16-item psychological inventory developed by Jackson (1984) to assess four different traits, i.e., “Nurturance”, “Affiliation”, “Autonomy”, and “Achievement”. His results show that PTs predict motivation for childbearing differently by gender. These differences have been confirmed by more recent studies. “Agreeableness”, together with “Extraversion”, is shown to positively predict parenthood among Dutch women, but not for men (Dijkstra and Barelds, 2009). Jokela et al. (2011) show that low levels of “Neuroticism”, high levels of “Extraversion” and high “Openness” associate with higher fertility for both genders, whereas high “Agreeableness” and low “Conscientiousness” are associated with higher female fertility. Moreover, Jokela et al. (2009) find that low levels of “Neuroticism” and high levels of “Extraversion” are associated with higher fertility in a 9-year follow-up study on a sample of Finnish men and women aged 15-30 years at the base year. White et al. (2019) explore the relation between PTs and sexual frequency and find a strong positive relationship of “Extraversion” for both sexes and “Conscientiousness” and “Agreeableness” for men. From the same sample instead, higher extraverted and less opened men have more offspring, whereas the same is found for more agreeable women. To our knowledge, there are only two studies on the relationship between fertility and PTs based on the German SOEP data set. One, by Lundberg (2009) finds that PTs predict fertility by age 30, whereas they apparently do not explain fertility history by age 40. This indicates that personality may matter more for the timing of fertility rather than for its completion. In another study, Le Moglie, Mencarini and Rapallini (2015) analyzed the effect of subjective well-being on fertility, controlling for PTs. Their results suggest that SWB is positively related to the likelihood of having a child. However, fertility turned out to be related both to subjective wellbeing and to PTs, though the latter do not unequivocally determine the reproductive behavior.

Summarizing, the effect of PTs on controlled fertility seems to be gender and age-specific, and when personality is measured using the Big Five, “Extraversion” tends to increase and “Neuroticism” tends to be more significant and depress fertility.

A related and interesting line of research argues that the relationship between fertility and personality might actually change across cohorts. The argument stems from the Second Demographic Transition (i.e., Van de Kaa, 1987), with the idea that the circumstances of childbearing has changed over time. For instance, younger cohorts have a greater freedom to pursue their own fertility interests, and childbearing is no longer the pillar of social control as it used to be. Consequently, one may expect PTs to play a stronger role today compared to what was the case in the past. Particularly for women, personality played a weaker role when society was characterized by the male bread winner model, with husbands and wives specializing in market and household work respectively. Instead, with educational expansion and greater equality in opportunities for men and women, the role of personality will necessarily become more important. Following this line of argument, Jokela (2012) finds that "Openness" for both genders and "Conscientiousness" for women only are particularly related to lower fertility among later-born cohorts in the US. Similarly, Skirbekk and Blekesaune (2013) using data from the Norwegian Generations and Gender Survey linked with a postal survey that collected information about personality traits, conclude that the personality–fertility relationship is different for more recently born cohorts who have experienced adult life in a different historical context. In fact, their main results are that "Conscientiousness" is associated with lower fertility for women, "Extraversion" is associated with higher fertility for men, whereas "Openness" and "Neuroticism" in men are associated with having fewer children. They also find that personality relates to fertility differently across cohorts, and that "Neuroticism" is negatively associated with fertility only for the more recently born male cohorts.

Personality can affect fertility also through its relationship with education, which has long been taken as the main predictor for fertility decline, due to the higher opportunity cost of childrearing and to its postponement (for the effect of education on German fertility, see Cygan-Rehm and Maeder, 2013). Yet, educational attainment is also mediated by PTs, which may, in turn, affect fertility. The massive educational expansion that has taken place over the last four decades, again, fuels the idea that the role of PTs on fertility might be different today compared to the 60s and the 70s. According to Tavares (2016), the influence of PTs both on education and on fertility decisions explains the fertility timing gap between more and less educated women. Using the BHPS, she finds that "Agreeableness", "Extraversion" and "Neuroticism" relate to early childbearing, while "Openness" and "Conscientiousness" relate to later childbearing. Even so, individual differences in PTs result in differences in the age at first birth, especially among more educated women, who postpone childbearing for longer.

An important insight in the study by Tavares, is that reproductive behavior is interrelated with other careers, such as educational choices. But other trajectories will also matter, and perhaps the most important ones are the process of entering into and eventually exiting a partnership and individuals' job careers. These life-course transitions influence each other and they are all dynamically intertwined meaning that they must necessarily be analyzed conjunctly (Elder 1985). As consequence, the association that we find between personality traits and fertility may very well mask the fact that personality affects at the same time (and even beforehand) the participation in education career, their success in job market, and their propensity and facility to find a partner. In fact, there is an extensive literature on the relationship between personality and selection into union formation and dissolution, as well as on working career.

The studies which analyze the relationship between PTs and union formation found significant correlations, again, as in the case of fertility, which are different by gender and by cohorts (from older to more recent cohorts of people). Diener and Lucas (1999), found that those personality traits that make one happier, such as high "Extroversion" and low "Neuroticism", are likely to attract a marriage partners. Lundberg (2012), looking at the effect of personality traits both on the formation and dissolution of partnerships, using German SOEP data, shows that selection into marriage is associated with distinctly different personality profiles for men and women born before 1960, whereas for younger cohorts the effects by gender are more similar. These results are consistent (also with the analysis by Lundberg) in the light of changes in couple organization that has evolved from a gender specialized, to having become more egalitarian and derived consumption based aspects. For older cohorts, born between 1945 and 1959, only "Extraversion" significantly increases the probability of marriage for both men and women, while agreeable women, and conscientious, antagonistic men, are more likely to marry. For younger cohorts, born between 1960 and 1970, two personality traits, "Openness" to experience and "Conscientiousness", have significant positive effects on the probability that men and women marry by age 35. Some other studies have investigated specifically the association between PTs and union dissolution (e.g., Kiernan, 1986; Lowell and Conley, 1987; Kinnunen et al., 2000). Personality seems indeed to be linked with long-term relationships quality. Divorce is associated with high "Neuroticism" and "Openness" and low "Conscientiousness" for both genders, low "Agreeableness" for women, male "Extroversion" (see Roberts et al. 2007 for a comprehensive review on this literature).

It also seems that among more recent couples women are more likely than men to monitor relationship quality and to end or avoid unsatisfactory consensual unions (Aberg, 2009). This implies that males' characteristics may be more important in term of union stability. The same, and even more when deciding on the very long term investment of having children, male personality characteristics may grow in importance relative to women's personality in predicting family formation and dissolution behavior (Lillard and Waite 1993; Hewitt, Western and Baxter 2006).

There is also a vast literature on personality differentials and job careers. Judge et al (2006), analyzing the Five-PTs model with respect to career success, found that “Conscientiousness” positively predicted intrinsic (i.e. job satisfaction) and extrinsic career success (i.e. income and occupational status), “Neuroticism” negatively predicted extrinsic success. Previously, Seibert and Kraimer (2001) surveyed employees in a diverse set of occupations and organizations to study PTs and career success and found that “Extraversion” was related positively to salary level, promotions, and career satisfaction and that “Neuroticism” was related negatively to career satisfaction. “Agreeableness” was related negatively only to career satisfaction and openness was related negatively to salary level.

Earnings and salary levels in particular are found by several studies to be linked with different personality for men and women. Using Dutch data, Nyhus and Pons (2005) and Mueller and Plug (2006), using American data, find that emotional stability is positively related to the wages of men and women, while “Agreeableness” is associated with lower wages for women. Heineck (2011) finds wage penalties for “Neuroticism” and “Agreeableness” for both male and female workers in the U.K. Nyhus and Pons (2005). The returns to personality factors vary both by tenure and by educational group, suggesting that different personality traits may enhance productivity in different occupations and that personality effect already starts with the different track and success in education.

3. Data

In this study we use the data from the German Socio-Economic Panel survey (SOEP), a representative ongoing longitudinal study started in 1984 (Wagner et al. 2007), and include in our analysis all the waves up to 2015. The SOEP is well suited for our analysis because the length of the study allows us to follow individuals over a relatively long period and because it contains longitudinal information on the three processes of interest, as well as on personality traits.

We build for each individual the three sequences of job career, union formation and fertility based on the yearly activities (states) experienced in each of the three domains between the ages of 20 and 40. Specifically, regarding job career, we use information on individuals’ labor force status to distinguish between full-time workers, part-time workers, in training (or education), unemployed and individuals not working. We map changes in partnership by relying on information about changes in individuals’ marital status, distinguishing between being single, married, and separated or divorced. We removed from the dataset widowed, because their partnership history cannot be regarded as the reflection of the PTs. As for fertility histories, we register the total number of children ever had by the individual (varying from 0 to 6). Since only few individuals have more than three children we only distinguished between 0, 1, 2 and 3 or more children.

As for the Personality Traits (PTs) scores, SOEP has surveyed those in three waves, namely in 2005, 2009 and 2015, every time using the 15-items personality inventory of the so-called "Big Five" PTs. These five factors are robust to factor analysis extraction and rotation approaches, stable across different cultures and languages and considered reliable to take into account for substantive co-variations in personality descriptions (McCraeand Allik, 2002; Gosling et al., 2003). There is also broad agreement about the labeling of the five traits: I) "Intellect" (or "Openness" to Experience – being imaginative, creative, curious and unconventional). II) "Neuroticism" (worrying, being nervous and emotionally unstable); III) "Extraversion" (attitude to being active, being forthcoming and desiring social relationships); IV)"Conscientiousness" (being systematic, goal-oriented and self-disciplined); and V) Agreeableness" (being friendly, warm and sensitive toward others).

For each individual in each of the three SOEP waves, the general trait scores are calculated by averaging the answers to a set of questions (three for each trait), in which the respondent assesses how well a descriptive phrase applies to her/himself using a 7-points Likert scale ranging from 1 ("The sentence does not apply to me at all") to 7 ("The sentence applies to me perfectly"). For those questions having inverse (expected) relation with the underlying trait, the scale of the answers was reverted before averaging.

Finally, to reduce the possible noise due to the use of a specific wave, for each individual we averaged the value of each PT score across the three waves. This is possible because, as demonstrated by Le Moglie et al., (2015) also using SOEP data, the PTs in the age range 20-50 remain quite constant.

The other independent variables employed as controls in the second part of our analysis include a set of dummies indicating: the macro region where the individual lives (i.e. North, South, West or East Germany), if both parents are immigrants, the respondent's father's and mother's level of education (i.e. secondary or not) and the household's income in the last month. A detailed list and description of all the variables employed in the analysis is provided in the Appendix.

4. Identifying typical careers using Multichannel Sequence Analysis

Information about the complete trajectories was available on 967 individuals (482 men and 485 women) continuously interviewed every year between the ages of 20 and 40. Some attrition was caused by missing values on the control variables. We started analyzing the sequences in the three domains using the typical tools available in sequence analysis. For each domain, we built a dissimilarity matrix whose elements are the dissimilarities between all the possible pairs of sequences. Following a rather standard approach, we used the Optimal Matching (OM) algorithm (Abbott, 1995) to measure the dissimilarity between two sequences as the effort needed to transform one sequence into another. Specifically, three basic operations are considered for transformation: insertion of a state, deletion of a state, and substitution of a state with another. To each operation, a cost is assigned, and the transformation cost is measured as the minimum total transformation cost (sum of the costs related to each operation). The choice of the costs is arbitrary, and there is no generalized consensus or a universally accepted criterion. Here we set the insertion and deletion (indel) costs both equal to 1, a criterion that is common in the literature, and the substitution costs inversely proportional to the frequency of transition from one state to another.[1] In this way, substituting a state with another is less costly when frequent transitions between the two states are observed in data.

Figure 1 reports the index plots of the sequences in the three considered domains for individuals with no missing values (357 women and 361 men), distinguishing between men and women. In these plots, individuals are placed on the horizontal axis, and to each individual a vertical bar is associated, describing the activities experienced in the considered period (reported on the vertical axis, here the years from the age of 20 to the age of 40); different colours are assigned to the different activities. Column-wise individuals (men in the left-side plots and women in the right-side plots) are ordered on the horizontal axes according to the number of *children* and to the age at their birth. This allows emphasizing the relation between the sequences in the partnership and in the job domains and those in the children domains, which is somehow focal in our analysis.

<please insert Figure 1 about here>

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[1] More precisely, we set the cost of substituting state *a* with state *b* and vice-versa as $s_{ab} = 2 - p_{a \to b} - p_{b \to a}$, where $p_{a \to b}$ is the frequency of transitions from state *a* to state *b* in the data.

The index plots suggest some interesting preliminarily considerations. First, a substantial difference can be observed between the sequences of men and women. Men tend to postpone to later age marriage and parenthood. As for the job careers, a higher proportion of women have careers dominated by part-time work and by unemployment or NEET (i.e., not in education, employment, or training), with a higher tendency to switch to such activities when they become mothers at an early age or when they have a relatively high number of children. A very different tendency is observed for men, who tend to experience much more stable careers, usually working full-time, even when having a relatively large family. The apparent difference between women and men' careers suggests the opportunity to apply cluster analysis separately for men and women (in order to avoid gender-based clusters).

Second, the three domains appear connected. Indeed, individuals with similar careers in one domain tend (on average) to experience similar careers also on the others. This is particularly true for women, whose job careers are clearly related to the family formation domains. The job careers of the men tend to be slightly less connected to the other domains: as expected, men tend to work – most frequently full-time – even when they have a family. On the one hand, this further supports the choice of analyzing women and men separately. On the other hand, this evidences that the three domains should be considered jointly, so as to identify the most typical *combinations of family and job careers* experienced by individuals in the sample. To do so, we decided to apply multiple Sequence Analysis, combining information on the careers defined on the three domains into a unique *joint* dissimilarity matrix.

Specifically, we refer to the so-called multichannel Sequence Analysis (MSA) developed by Pollock (2007), who suggests to extend optimal matching (OM) to multiple sequences by averaging the substitutions (and indel) costs needed to align the sequences in each domain. This approach extends the rationale underlying OM to the case of multiple domains, also preserving the information on each domain, as measured by the specific transformation costs. Based on the joint dissimilarity matrix obtained in this way, clusters of individuals experiencing similar careers on the three domains, can be obtained, and the probability of cluster membership can be related to PTs via multinomial logistic regression.

The relatively low number of complete trajectories available for the two subsamples of women and men implies small sample sizes, possibly lowering the possibility to obtain well distinguished clusters with a decent size. It may also affect power, thereby making it more difficult to establish significance of the conclusions that can be drawn based on the logistic regression. In addition, this leads to exclude from the analysis the younger cohorts, who had not yet turned 40 at the moment of the last available interview.

4.1. A new approach for the Sequence Analysis of trajectories of different lengths

To avoid the potential weaknesses associated to the exclusion of shorter trajectories from Sequence Analysis, we develop a new procedure to evaluate the dissimilarity between sequences of different lengths (or, more precisely, right-truncated or censored). This allows us to include in our analysis also individuals whose trajectories were observed only for a limited time span, because of censoring or (more importantly) because they were younger than 40 at the last wave. Specifically, besides those individuals who were observed for the entire observation period (between 20 and 40 years of age), we also consider individuals who were observed *at least* between 20 and 30 years of age, thus including in the analysis sequences with lengths ranging from 10 to 20 years. This implies an increase in the number of individuals included in the sample (1183 women and 1116 men).

To evaluate the pairwise dissimilarity between two sequences of different lengths we propose to focus on the period of observation common to them (that is the longest period – starting from the age of 20 – available for both cases). More precisely, we consider the set of joint dissimilarity matrices, $\mathbf{D'}_{20:t}$, with t = 30, 31, …, 40, obtained by applying multichannel sequence analysis to the complete sub-sequences observed over the age spans 20-30, 20-31,…, 20-40. The (i, h)-th entry of each $\mathbf{D'}_{20:t}$ is not missing only if the i-th and the h-th individuals were both observed (at least) between the age of 20 and the age of t. Since the size of the elements of the obtained dissimilarity matrices might depend (also) on the length of the sequences they are based upon, we normalize each matrix dividing its elements by the length of the considered sub-sequences, defining $\mathbf{D}_{20:t} = \mathbf{D'}_{20:t}/(t - 20 + 1)$. For two individuals, say the i-th and the h-th, observed over a different age span, e.g. from 20 to t_i and from 20 to t_h respectively, we set their dissimilarity equal to the (i, h)-th element of $\mathbf{D}_{20:\min(t_i,t_h)}$, which is clearly available and not missing. Proceeding in this way, we obtain what we call the *integrated* dissimilarity matrix, $\mathbf{D}^*$, whose elements are the dissimilarities calculated based on the maximum common age span available for each pair of cases..

Before proceeding, it is worth mentioning that some elements of the dissimilarity matrix $\mathbf{D}^*$ do not satisfy the triangular inequality. This does not prevent the use of such dissimilarities in cluster analysis. Indeed many dissimilarity criteria are frequently employed that do not satisfy such condition, and are therefore not metrics (e.g., the Jaccard coefficient or other coefficients used to measure the dissimilarity based on categorical data, or the Bray-Curtis coefficient typically used to cluster ecological data, see Everitt, 2003, for details).

Even so, for the sake of completeness, we also considered two alternative procedures that could be employed to define dissimilarities based on sequences of different length.

A first possibility consists of referring to clusters obtained based only on cases presenting complete sequences. To each cluster, its medoid (Kauffman and Rousseeuw, 1990; Aassve et al., 2007) is associated, i.e. the case presenting the smallest dissimilarity to all the other cases in the cluster itself. Cases with truncated sequences can subsequently be assigned to each cluster based on their dissimilarities with the corresponding clusters' truncated medoids. Thus, the dissimilarity between a case observed only between the age of 20 and of t and the obtained clusters is evaluated as the dissimilarity between the sequence and the medoids' trajectories observed between 20 and $t$years of age, and the case can be assigned to the cluster whose medoid it is closest to. To avoid an excessive dependence of the assignment procedure on the medoids representing the clusters another possibility consists in evaluating the dissimilarity between a truncated sequence and a cluster as the average dissimilarity between the case and all the (complete) sequences in the cluster truncated at t. The main drawback of these approaches is that the clusters' quality (e.g., the average silhouette coefficient, the R-square or other criteria used to monitor partitions with a different number of clusters) would be evaluated referring to the reduced set of complete sequences and not to the entire set of sequences allocated to the obtained clusters. More importantly, from a substantive point of view, the complete sequences would clearly lead the clustering process and in the case when shorter sequences (characterizing for example younger cohorts) exhibit trajectories whose features differ from those characterizing the (initial track of the) complete trajectories it would not be possible to build clusters accounting for such features.

Another possibility consists in extracting a distance matrix from $\mathbf{D}^*$, limiting attention to its "Euclidean" portion (see McArdle and Anderson, 2001), or adjusting it to correct for its non-Euclidean portion (see Gower and Legendre, 1986; Legendre and Anderson, 1999). This can be done by preliminarily applying metric multidimensional scaling (MDS), and by focusing only on the factors corresponding to positive eigenvalues or applying a correction for negative eigenvalues (specifically, an additive constant can be computed and added to the non-diagonal dissimilarities such that the modified dissimilarities are Euclidean). In both cases, a matrix of numerical variables would be available, which can be clustered using a *k*-means algorithm rather than PAM.

4.2. Clusters of trajectories for the SOEP data

Using the procedure described in the previous section, we built the integrated dissimilarity matrices $\mathbf{D}^*$ for the two sets of women and men. We extracted a number of clusters ranging between 2 and 15 using the *partitioning around medoids* algorithm (PAM; Kauffman and Rousseeuw, 1990). As underlined by Piccarreta (2017), a great deal of caution is necessary when evaluating partitions obtained based on a compromise dissimilarity matrix (combining dissimilarities in different domains). Indeed, it is possible that the less 'turbulent' domains (that is domains where the careers are relatively more stable) prevail. We therefore monitored three rather standard measures of adequacy, namely the R-square, the Point Biserial Correlation, and the average silhouette coefficients (Kauffman and Rousseew, 1990) calculated based on the joint (multichannel, MSA) integrated dissimilarity matrix, $\mathbf{D}^*$, and on the domains-specific integrated dissimilarity matrices, D_J^*, D_P^*, and D_C^* obtained by applying the same procedure described in the previous section to each domain separately. The results obtained for women and men – reported in Figure 2 – show that both for women and for men, the work domain is not particularly well explained. Indeed, this is the most turbulent domain, with a higher number of states and less stable sequences (see Figure 1). Instead, the partnership and the parental domains are better explained and – particularly for women – clusters based on the joint dissimilarities are able to explain them simultaneously, as one can reasonably expect because of their relatively strong association (see Figure 1). Notably, the average silhouette coefficients tend to decrease with the number of clusters, pointing to possibly over-simplified partitions.

<please insert Figure 2 about here>

Indeed, a close inspection of the resulting partitions evidenced that simple partitions were indeed able to identify clear patterns in the partnership and parenthood domains but did not allow a clear representation of the different work trajectories in data. As a matter of fact, the turbulence of the work domain can lower down the values of the clusters' quality indicators (as well as the improvements in clusters' quality consequent to a refinement of the partitions). In addition, since our intent is to relate clusters to PTs via multinomial logistic regression, it is important to extract a number of clusters high enough to identify common patterns in all the domains. To select the number of clusters for women and men, we focus on partitions corresponding to a stabilization of the quality indicators, particularly with respect to the work domain, as well as on a close inspection of the clusters' structure. Based on these considerations, we select 6 clusters for women and 7 clusters for men as reasonable compromise solutions.

Figures 3 and 4 report the index plots of the sequences in each domain for each cluster. To enhance the visualization of the sequences in the plots, the ordering of the individuals in each cluster along the horizontal axis was determined using a seriation algorithm based on the joint dissimilarities characterizing the cases in the cluster itself (the arrangement of individuals along the horizontal axis is the same for each domain cluster-wise). The plots confirm the previous observations about domains' turbulence and support the choice of the considered partition.

<please insert Figures 3 and 4 about here>

It is interesting to observe that our novel procedure to cluster individuals based on sequences having different lengths performs satisfactorily. Indeed, cases placed in the same clusters have similar initial common tracks. In fact, truncated sequences are observed corresponding to women who exited the panel before turning 40, or who were aged less than 40 at the moment of the last available wave. Even if some clusters – e.g. clusters 1 and 2 – present a relatively higher proportion of shorter careers, women in these clusters all show a tendency to postpone family formation, because on average they remain single and without children till 30 years of age or more, and they show a stable participation to the labor market (even if under different working conditions). In the same way, all the cases placed in the other clusters present similar careers – or at least similar initial patterns – irrespective of the length of the observation period.

For the sake of completeness, we also applied the two alternative procedures illustrated in the previous section. We first applied the PAM clustering algorithm to the multichannel dissimilarity matrix built based only on cases observed for the entire observation period. We then assigned cases with truncated sequences to the closest cluster, by measuring closeness to cluster as the average multichannel dissimilarity between the sequence and all the sequences within the cluster truncated to resemble its length. As mentioned before, in this case monitoring the performances of partitions of different degree would be not informative because they would refer to the explanatory ability evaluated with respect to the complete sequences only. Therefore, we decided to focus on the comparison between the partitions of 6 and 7 clusters for women and men respectively with those obtained based on the integrated joint dissimilarities. Results (displayed in Figures A1 and A2 in the Appendix) are not particularly satisfactory, particularly with respect to the work trajectories. Indeed, for men this procedure was not able to isolate in a dedicated cluster individuals who periods or repeated events of unemployment. Also as for women results are worse than those displayed in Figure 3 particularly, again, for the work domain.

We also resorted to procedures aiming at building Euclidean distance matrices based on the integrated joint dissimilarities. We applied MDS, and we extracted a number of factors coinciding with the number of positive eigenvalues; we also applied a correction for negative eigenvalues by adding to the non-diagonal elements of the original dissimilarity matrix a constant such that the modified dissimilarities are Euclidean. From the modified matrix a set of MDS factors can be extracted that reproduce it perfectly. In both cases, based on the available set of MDS factors we obtained clusters using both the PAM algorithm and the *k*-means algorithm. Again, since the algorithms are applied to dissimilarities different from the original ones, it is not possible to compare the performances of the resulting partitions, and we therefore decided to contrast the 6- and 7-clusters partitions obtained for women and men respectively using alternative approaches. The most relevant differences – as reasonably expected – were observed corresponding to the solutions based on the MDS factors corresponding to the positive eigenvalues extracted from the original integrated dissimilarity matrices. Such partitions can be convenient because they give more importance to the first and most important factors extracted from the original dissimilarity matrices. Nonetheless, this implies disregarding those differences, and in this respect moving away from the principles underlying Sequence Analysis itself. In the end we found that the clusters obtained using our procedure were somehow easier to interpret – particularly with respect to the combination of the trajectories experienced in the three domains. In addition – and notably – results obtained after correcting for negative eigenvalues lead to results identical to ours when PAM is used and very similar to ours when *k*-means is used.

For this reason, in the following we will focus on the clusters based on the integrated dissimilarity matrices $\mathbf{D}^*$ built for the two sets of women and men.

4.3. A substantive interpretation of the clusters

In this section we offer a substantive interpretation of the clusters obtained for women and men.

The six clusters extracted for women (Figure 3) are characterized by very clear and distinctive features.

Cluster 1: "Single and childless full-time working women". This cluster includes a number of truncated trajectories higher than the others. Thus, individuals in this cluster are not surveyed until the age of 40, because they exited the survey or because they were younger than 40 at the last wave. The job trajectories show a clear prevalence of women working full-time, while the trajectories of partnership and parenthood show a net prevalence of women who remained single and childless until the age of 30, few of whom married and/or had children after. Even if it is not possible to assume the existence a causal effect, one might hypothesize the desire/necessity to have a stable work before forming a family to be at the basis of the postponement of family formation.

Cluster 2: "Un-married childless women not in job career". This cluster differs from cluster 1 mainly with respect to the job trajectories, characterized by an initial track spent in education or training. Interestingly, in this cluster there are also women who enter the labor market with a part-time job (not motivated by the presence of children), and who – in some cases – get a full time job only after the age of 25. *Cluster 3: "Mothers of few children with unstable working conditions"*. This group is quite different from the first two ones. The job trajectories appear rather turbulent with frequent transitions across different job conditions, even if with relatively long spells in part-time working. Most of these women had their first child before the age of 25, and only few had a second child (between the age of 28 and 30 in most cases). These women are mainly non-married, even if possibly they are in a cohabitation. Interestingly, the cluster includes a significant proportion of separated or divorced women.

Cluster 4: "Working women, married later, with few children". This cluster is well delineated in all the three trajectories. Women in this group are mainly working full time with long and stable working spells. As for the family formation domains, we observe a vast majority of married mothers of one/two children, who, compared to women in clusters 4 and 5, postponed marriage and motherhood, probably because they invested on their job career before.

Cluster 5: "Early married housewife with large families". This group identifies women whose trajectories have unique characteristics in all the three domains. They are mainly non-working women (or they work only for very short spells), and, compared to other clusters, they anticipated the family formation. Indeed, they married before the age of 20 and had their first child before the age of 25 (on average). Notably, this cluster includes almost all the women who had at least 3 children,

Cluster 6: "Working married mothers with large families". This cluster identifies married women with relatively big families (one or two children) who try to combine family and job working part time. Their age at family formation is intermediate between cluster 4 and cluster 5. Indeed, some of them entered the labor market with a full-time job before getting married and having children, and this might explain the slight postponement of family formation with the latter "renounce" to a full-time career when the dimension of the family increased.

Turning to the 7 clusters obtained for men (Figure 4), note that the first four clusters all include individuals who remained unmarried (but could be possibly in a cohabitation) and without children for the entire period of observation and, notably almost all the truncated trajectories, which might possibly characterize men who were younger than 40 at the age of the last interview. Based on their different work trajectories, these groups can be labelled as follows:

Cluster 1: "Single-childless full-time working"

Cluster 2: "Single-childless men working part-time"

Cluster 3: "Single-childless male in training or education".

Cluster 4: "Single-childless men unemployed".

Individuals placed in the last three groups are mainly working full-time. Based on the differences with respect to the partnership and fatherhood careers, we have:

Cluster 5: "Later married- working fathers with few children". In this group men married later (and sometime also separated or divorced) and have (few) children later.

Cluster 6: "Working married fathers with one/two children"

Cluster 7: "Early married working men with large families".

5. Multinomial Analysis: The Effect of Personality on Individuals' Trajectories

In this section we describe the results obtained by analyzing the relation between PTs and clusters – controlling for a set of socio-demographic variables – using multinomial logistic regression.

In the second part of the analysis we apply a multinomial logistic regression to establish, separately for women and men, how the five PTs relate to the probability of belonging to the clusters previously described. For estimation of the multinomial regression model we model the probability of belonging to the g-th cluster conditionally to a set of covariates $\mathbf{x}$ as $\exp(\mathbf{x}\boldsymbol{\beta}_g)/[1+\sum_{h=1}^{G}\exp(\mathbf{x}\boldsymbol{\beta}_h)]$, where $g = 1, \dots, G$, $\mathbf{x}$ is a K-dimensional row vector with first-element unity, and $\boldsymbol{\beta}_g$ that is the K-dimensional vector of unknown parameters associated with the considered covariates, that can be estimated using the maximum likelihood approach. In our case, the vector of covariates includes the five PT scores and the set of controls variables introduced in Section 3.

To ease the evaluation of the possible impact of the PTs on the clusters, instead of the regression coefficients, which relate non linearly to the probabilities, we calculate the average marginal effect of each PT score on the clusters' membership probabilities. The results are plotted separately for men and women in Figures 5 and 6[3].

<please report Figures 5 and 6 about here>

At a first glance the analysis of the two figures together seems to reveal that personality matters more for the trajectories of men than for those of women. Moreover, among the five traits, "Consciousness" and "Openness" matter significantly for both genders. Instead for women, the probability to belong to cluster 2, i.e. to be "un-married childless women, not in job career" is negatively and significantly associated to consciousness and positively to openness (with a weak negative association also with extroversion). Higher consciousness has a positive effect on belonging to the cluster 4, i.e. "working women, married later, with few children", whereas on the contrary, consciousness is significantly and negatively associated with being "early married housewife mothers with children".

As for men, "Consciousness" is negatively and significantly related with the probability to end up both into cluster 2 ("childless/single men with unstable working careers") and 4 ("single/childless men unemployed"), and positively with cluster 6 ("working fathers in union with one/two children"). "Openness" is positively related with cluster 3 ("single-childless male students") and negatively with cluster 6. In addition, differently from women, for men also "Neuroticism" and "Extroversion" appears to play a role. Specifically,

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[3]For sake of brevity, we avoid to present the regression results of the multinomial logit. Nonetheless, they are available upon request, together with the numerical evaluations of the marginal effects used to obtain Figures 5 and 6.

neuroticism is positively related with cluster 4 ("single/childless men unemployed") and positively with cluster 3 ("single-childless male students"), whereas a higher "Extroversion" score significantly decreases the probability of belonging to the same cluster 3 ("single-childless male students"). Extroversion (together with "Consciousness") is positively and significantly associated with the cluster 1, i.e. "single-childless full-time working men".

Cluster 3, identified as "single-childless male students", we find a positive relationship with "Openness" and "Neuroticism". In contrast, a higher "Extroversion" score significantly decreases the probability of belonging to this cluster. For cluster 4, "single/childless men unemployed", individuals are less likely be characterized with the "Consciousness" trait, and positively related to "Neuroticism". Cluster 5, identifying "later married- working fathers with few children" seems related negatively to "Openness" and positively to "Extraversion", but the effect are not very strong and significant. Cluster 6, on the contrary, of "working fathers in union with one/two children", is clearly related to men with low "Openness" and high "Consciousness". Cluster 7 "early married working men with two or three children" is not identified by any PT.

6. Conclusion

In this study we demonstrate that certain personality traits, here measured by the "Big Five" inventory is associated with certain life course paths. The idea is that personality, which is proved quite stable during reproductive ages, i.e. from 20 to 50 (see Le Moglie et al. 2015), shape individuals' entire life course. Previous literature has focused on specific events such as educational careers, job careers, union formation and dissolution and not least, childbearing. In contrast to this literature, we demonstrate here that personality traits matter in the way individuals end up in particular life course trajectories. This is an important contribution and insight since it is not obvious that personality matters directly for those observed events. Rather, personality appears to be significant for ending up in specific types of life course trajectories – of which education, jobs, union dynamics, and, fertility are components. In other words, personality may matter for the frequency of events across all domains, or, personality may matter in terms of postponing one event – but accelerating others.

We find that PTs shape significantly some life course trajectories, though not for all. Moreover, there are important differences for men and women. For women we find the "Consciousness" trait to play an important role. When it is high, women are much less likely to end up in cluster 2. In other words, women in cluster 2 tend to score low on this trait. They have problems in entering the job market, but are less likely to remain un-partnered. Still considering the same cluster, a high score on “Openness” associates with women not being married and again potentially struggling in their job career. They also are much less likely to have children. However, also for women in cluster 5, which arguably is the high fertility cluster, we also find a lower consciousness score. This result is consistent with Jokela (2011), though here we find in addition that women in this cluster also tend to marry and have low attachment to the labor market. In other words, the low score of “Consciousness” associated with higher fertility, is in part explained by weaker job careers. Consistent with these findings, we also see that a high score on “Consciousness” gives a higher likelihood of belonging to Cluster 2 – though the effect is not significant at the 95% level. Still, Cluster 4 is the antithesis of cluster 2, since the former is associated with marriage and stronger attachment to the labour force (though not with children).

As we showed PTs are potentially more important for men compared to women. Also for men, we found the “Consciousness” trait to play an important role. A low score makes men more likely to be in Cluster 2, which is characterized by childlessness and unstable working careers. A high score on “Consciousness”, in contrast, brings about a higher likelihood of belonging to cluster 6, which is characterized as working fathers with one or two children. In other words, stronger “Consciousness” among men, does not only bring about success in the job market, these men are also more likely to have children. One cluster that is particularly driven by PTs, is cluster 3, which is characterized by single-childless men. Here a high score on “Openness” is important, whereas a high score on “Extroversion” brings about a lower likelihood of belonging to this group. Finally, men in this group also score higher on “Neuroticism”. It is also worth noticing that not all personality traits matter for men’s life course trajectory. For instance, “Agreeableness” is never significant for any of the identified clusters. We also find two clusters in which PTs do not appear to be very important: these are clusters 1 and 7, both characterized by full time working men. In the first cluster, men do not have children, whereas in cluster 7, they have two or more children. As such, it appears that personality has an impact on those clusters which represents deviations from the full-time working norm.

In sum, the study confirms many of the previous studies linking personality traits to fertility, but what we see here is that those same personality traits are intrinsically linked with union formation (and dissolution) and men and women’s working career. The study also introduced an important technical innovation. As is common for this line of study, observed sequences are frequently short, meaning that many have not been able to complete the relevant domains that form the overall sequences. In the method applied here, we make a direct adjustment for this shortcoming, thereby increasing the sample by also incorporating those individuals with short sequences.

Appendix: List of all the variables employed in the models

- Marital status:
  Individual's marital status. We distinguish between single, married, and separated or divorced.
- Labor force status:
  Individual's labor force status. We distinguish between full-time workers, part-time workers, in training or education, unemployed and not working individuals
- N. Children:
  Total number of children ever had by the individual. We distinguish between 0, 1, 2 and 3 or more children.
- (O) Openness:
  Openness score. The score is calculated as the average of three questions asked in 2005, 2009 and 2015. The questions are: "Original", "Have lively imagination" and "Value artistic experiences". The answers are on a 7-point Likert scale ranging from 1 (Doesn't apply to me) to 7 (Applies fully to me). The final score for each individual is the average over the waves.
- (N) Neuroticism:
  Neuroticism score. The score is calculated as the average of three questions asked in 2005, 2009 and 2015. The questions are: "Deal well with stress", "Somewhat nervous" and "Worry a lot". The answers are on a 7-point Likert scale ranging from 1 (Doesn't apply to me) to 7 (Applies fully to me). The answers to the questions with negative meaning are reverted before taking the average. The final score for each individual is the average over the waves.
- (E) Extroversion:
  Extroversion score. The score is calculated as the average of three questions asked in 2005, 2009 and 2015. The questions are: "Communicative", "Sociable" and "Reserved". The answers are on a 7-point Likert scale ranging from 1 (Doesn't apply to me) to 7 (Applies fully to me). The answer to the question with negative meaning is reverted before taking the average. The final score for each individual is the average over the waves.
- (C) Consciousness:
  Consciousness score. The score is calculated as the average of three questions asked in 2005, 2009 and 2015. The questions are: "Thorough worker", "Tend to be lazy" and "Carry out tasks efficiently". The answers are on a 7-point Likert scale ranging from 1 (Doesn't apply to me) to 7 (Applies fully to me). The answer to the question with negative meaning is reverted before taking the average. The final score for each individual is the average over the waves.
- (A) Agreeableness:
  Agreeableness score. The score is calculated as the average of three questions asked in 2005, 2009 and 2015. The questions are: "Sometimes too coarse with others", "Able to forgive" and "Friendly with others". The answers are on a 7-point Likert scale ranging from 1 (Doesn't apply to me) to 7 (Applies fully to me). The answer to the question with negative meaning is reverted before taking the average. The final score for each individual is the average over the waves.

- Birth cohort:
  Individual's birth cohort. We distinguish between those born in 1964-1969, 1970-1974, 1975-1979 and 1980-1985.
- Immigrants:
  A dummy which is equal to 1 if the individual's parents are immigrants and 0 otherwise.
- Father's education:
  A dummy which is equal to 1 if the individual's father has secondary education and 0 otherwise.
- Mother's education:
  A dummy which is equal to 1 if the individual's mother has secondary education and 0 otherwise.
- Household's income:
  The total income received by the individual's household in the last month. It includes labor income as well as income from rent and dividend.
- Region:
  The German macro-region of individual's residence, that is North, South, West or East Germany.

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Figures

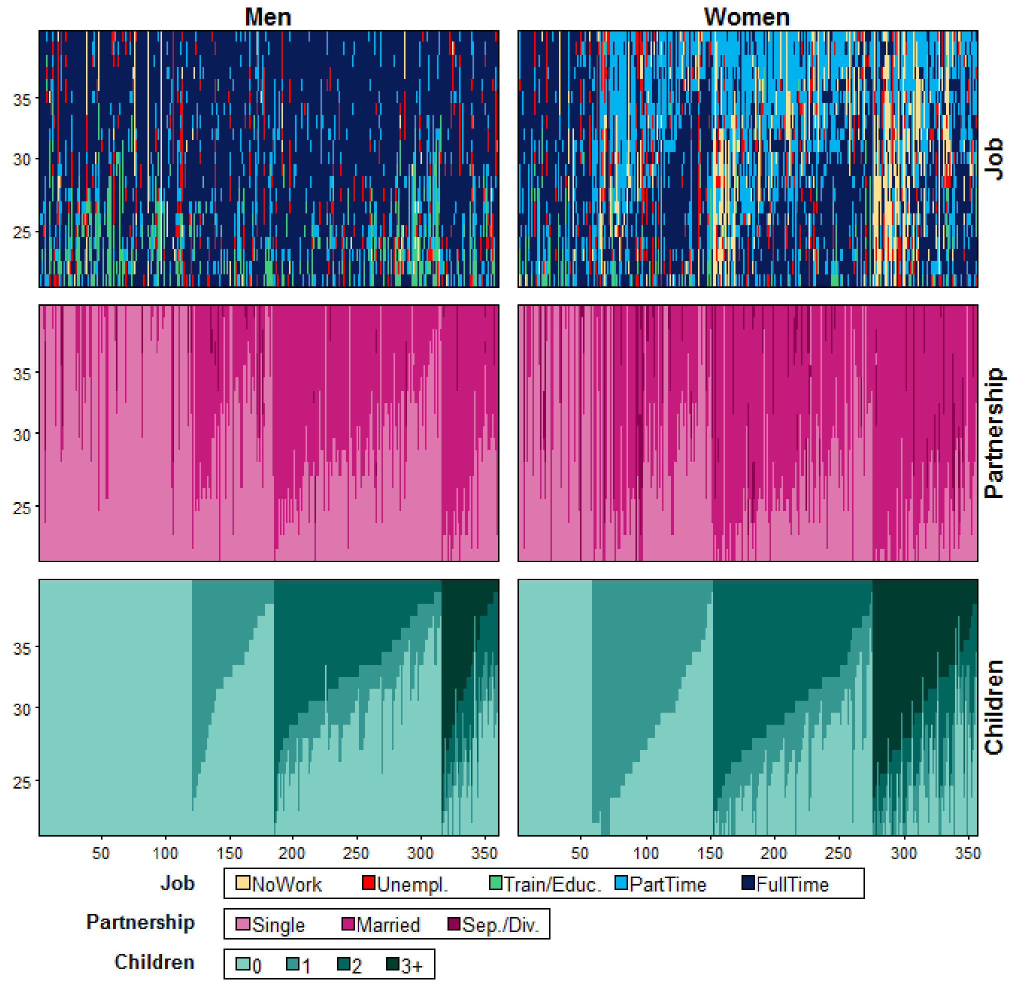

Figure 1. Index plots of the complete sequences – observed between 20 and 40 years of age – in each domain for men and women. For each gender, cases are ordered on the horizontal axes according to the *number of children* and to the parent's age at their birth.

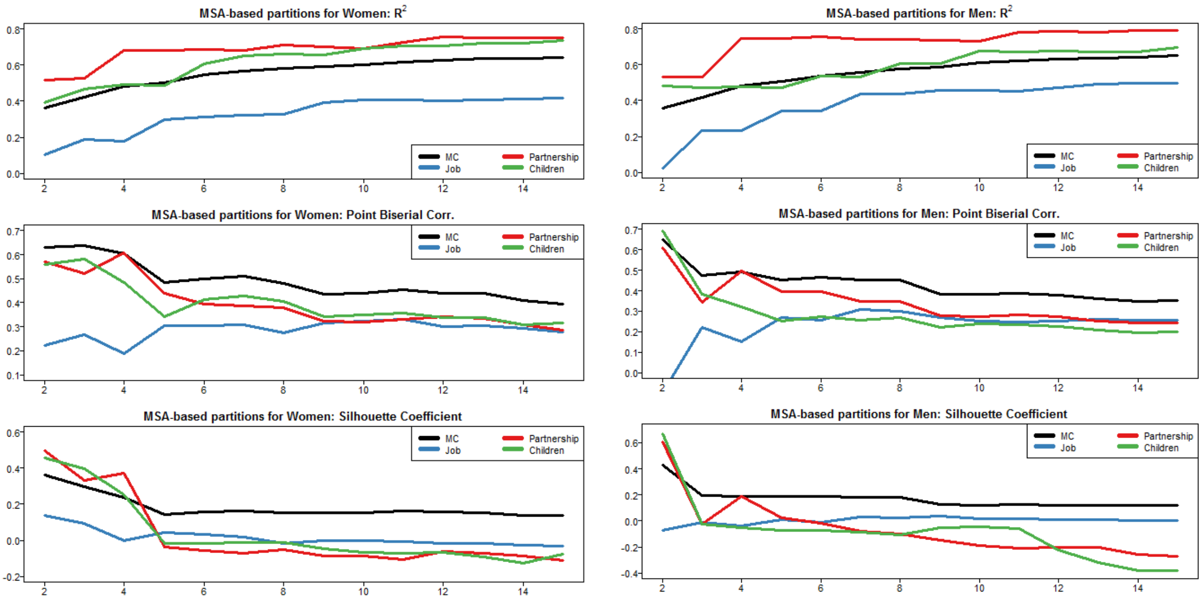

Figure 2. Monitoring the R-square, the Point Biserial Correlation, and the Average silhouette coefficients for a number of clusters ranging from 2 to 15 extracted applying the PAM algorithm to the multichannel integrated dissimilarity matrix D* built for women and men. The indicators are calculated based on the joint integrated dissimilarity matrix D* and also on the integrated dissimilarity matrices, D_J^*, D_P^*, and D_C^* obtained separately for each domain.

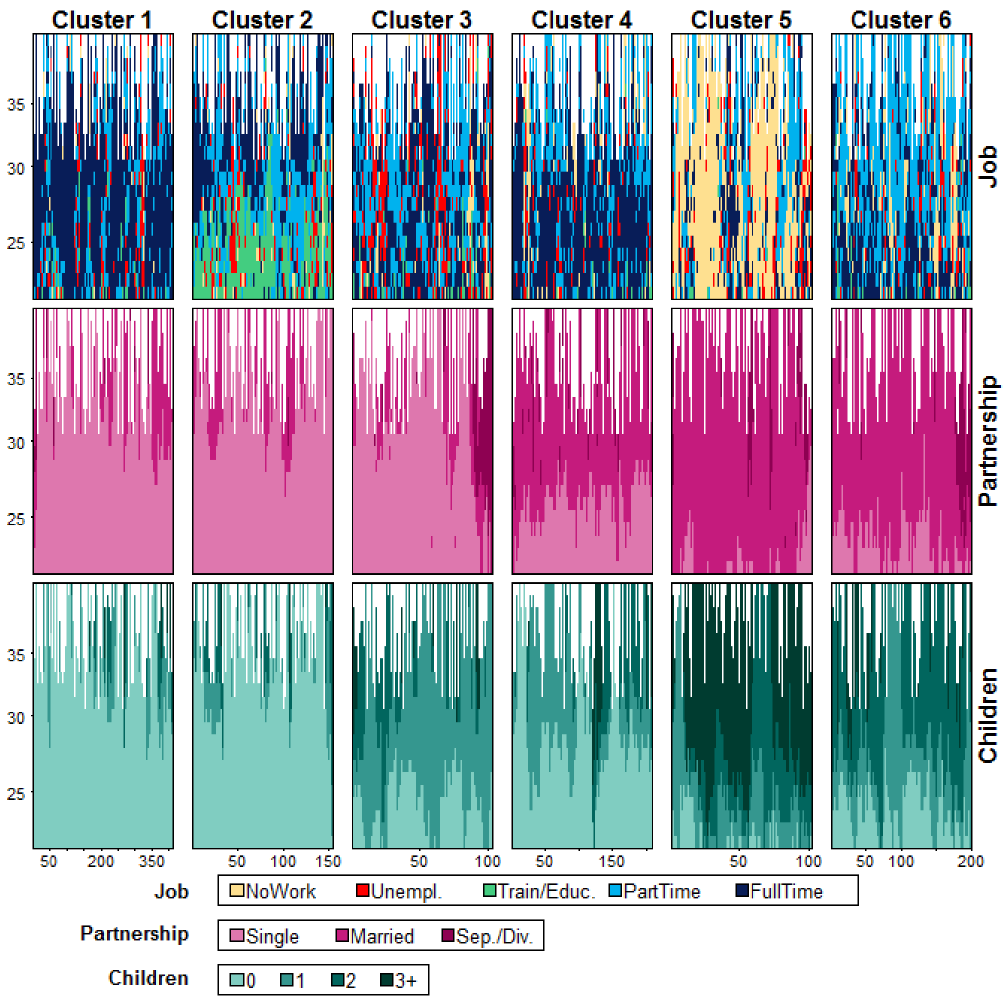

Figure 3. Index plots of the sequences for women in the three considered domains conditioned to the-clusters extracted using the partitioning around medoids algorithm.

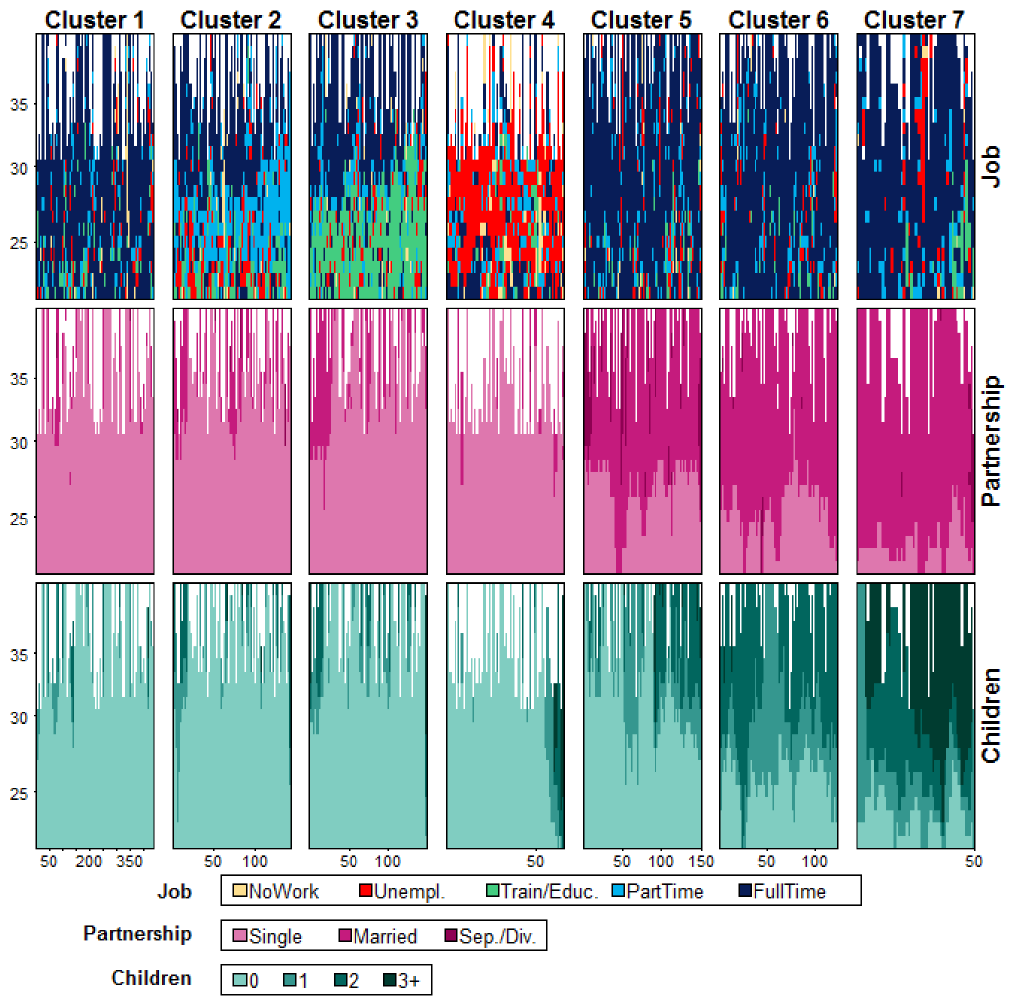

Figure 4. Index plots of the sequences <u>for men</u> in the three considered domains conditioned to the-clusters extracted using the partitioning around medoids algorithm.

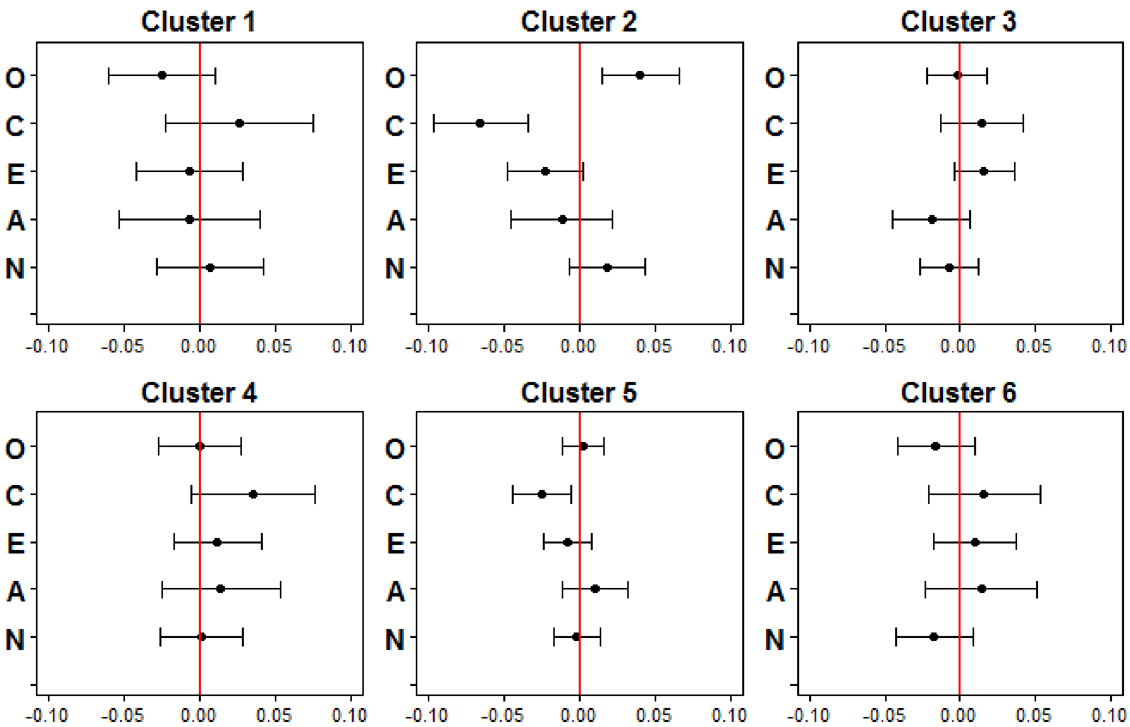

Figure 5. Women: Marginal effect of PTs on the probability to belong to a specific cluster together with the 95% confidence intervals.

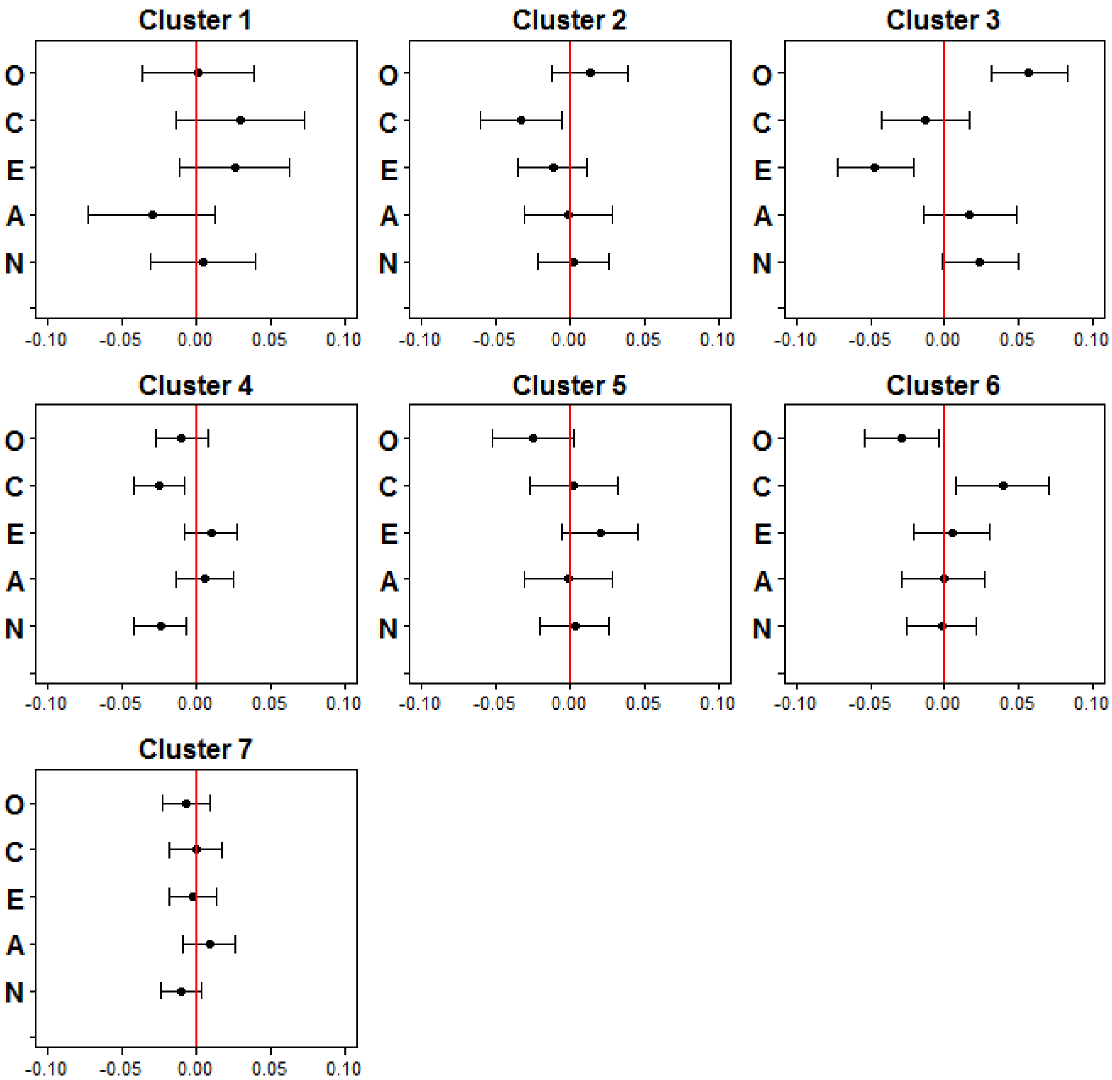

Figure 6. Men: Marginal effect of PTs on the probability to belong to a specific cluster together with the 95% confidence intervals.