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Use of Panel Surveys to Measure Employment Precarity in a Cross-National Framework: An Integrated Approach to Harmonize Research Concepts and Longitudinal Data

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In this article, we introduce a novel approach to the measurement of employment precarity (EP) in cross-country research based on individual career data from national panel surveys. We conceptualize EP as sequences of three types of adverse labor market experiences: non-employment, frequent job separations, and low income from work. These experiences are a common element in existing definitions of EP, and may be studied using available panel survey data over a broad range of countries. We consider these experiences to be valid indicators of labor market disadvantage across countries with differing institutional arrangements. In our operationalization of EP, we build upon recent developments in the field of sequence-based indices, and develop a Cross-National Precarity Index (CNPI), which quantifies and combines the persistence, intensity, and recency of each adverse experience throughout an employment sequence. We then provide an empirical illustration of the CNPI's performance in two countries with contrasting institutional regimes: Germany and the U.S., using data on employment biographies from the German Socio-Economic Panel (G-SOEP) and the National Longitudinal Survey of Youth 1997 (NLSY97). We examine the properties of the proposed measure by comparing the distributions of CNPI and its components in both countries, assessing the relationships between them, and analyzing the statistical association between the index and typical correlates of precarious employment identified in the literature: employment status (Germany) and access to social benefits (the U.S.). We conclude with a discussion of the possible applications and extensions of the CNPI, which provides a flexible analytical framework for comparative studies of employment precarity.

Keywords: precarity index; precarious employment; life-course approach; sequence-based measures; cross-national comparisons; longitudinal data

1 Introduction

The goal of this study is to introduce an analytical framework for the measurement and analysis of employment precarity (EP) in a cross-country perspective using individual career data from longitudinal surveys. We propose a comparable operationalization of EP in labor markets that differ in organization and legal regulations, based on data describing individuals' employment situation at multiple points in their work histories. We also provide a first assessment of the properties and performance of this measure in two countries with contrasting institutional arrangements: Germany and the U.S.

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The rise in precarious work has become a matter of concern for the social sciences (Kalleberg, 2009) as well as a major political issue (Standing, 2011). However, scientific inquiry into this subject, and especially policy relevant cross-national comparative research is complicated by the multidimensional and dynamic character of EP, which evades simple definitions and raises measurement problems (Armano et al., 2017; Olsthoorn, 2014). In this article, we claim that an adequate operationalization of EP at the individual level requires: (a) analyzing career sequences on the basis of longitudinal data rather than the employment situation at a single point in time, (b) taking into account data on the actual employment situation of individuals rather than their subjective evaluations of this situation, and (c) not relying on indicators of fixed-term employment, which are cross-nationally incomparable and lead to the restriction of cases included in the analysis to hired employees.

We conceptualize EP as a career pattern involving high job turnover, periods of joblessness, and low earnings, and develop a Cross-National Precarity Index (CNPI) for comparing the degree of precarity of various employment sequences based on these characteristics. The novelty of the CNPI lies in its focus on universal adverse labor market experiences, such as employment instability or being out of work, as opposed to the currently used indicators of country-specific types of employment relationships or contracts. These experiences reflect labor market disadvantage across different institutional contexts, which allows for cross-country analyses of EP.

We argue that the three experiences listed above capture key aspects of EP described in the literature, by allowing the measurement of the degree of attachment to the labor market of individuals and the level of economic security generated through work, regardless of their employment contract. Adopting a sequence-based approach is consistent with recent calls for analyzing career sequences rather than focusing on work characteristics at one point in time in studies of EP, to account for the changing dynamics and growing heterogeneity of occupational careers (Brzinsky-Fay, 2007; Fauser, 2020; Fuller & Stecy-Hildebrandt, 2015). However, we go beyond existing proposals for dynamic measurement of EP by including employer changes during periods of continuous employment, based on the argument that the lack of access to long-lasting jobs is an important aspect of precarious labor market situations, even when it does not affect employment continuity.

We propose and test a specific measurement approach for use with existing panel data to quantify the three types of experiences indicative of EP in terms of their persistence, intensity, and recency within an employment sequence. In this regard, the CNPI draws on and extends earlier indexes developed for the study of employment history sequences with the aim to capture precarity and other forms of labor market hardship (Busetta et al., 2019; Ritschard et al., 2018). The CNPI provides a flexible tool that can be accommodated to the needs of other researchers. The adverse experiences included in the composite index need not be restricted to joblessness, job terminations, and low income—other characteristics can be included, depending on data availability and the research questions.

The article is structured as follows. We start the second section with a critical consideration of the EP concept and its operationalizations and highlight the problems associated with using survey items like perceived job insecurity and type of employment relationship as measures of EP. In particular, we argue that using fixed-term employment indicators, which is the most common approach to capturing EP in many single- and multi-country analyses, does not allow for meaningful cross-country comparisons of this phenomenon, as it side-steps the problem of accounting for country-specific characteristics of various types of nonstandard work arrangements. In explaining our alternative conceptualization of EP, we refer to existing definitions of precarity and address the cross-country comparability of indicators included in the CNPI. Finally, we discuss existing sequence-based measures of economic hardship, and explain how the CNPI addresses their weaknesses. In the third section, we explain in detail the formula of CNPI, discuss the properties of each component of the index and the index as a whole, based on selected example sequences reflecting stylized types of labor market trajectories. In the fourth section, we provide an empirical illustration of the properties of CNPI using data from the German Socio-Economic Panel (G-SOEP) and the U.S. National Longitudinal Survey of Youth 1997 (NLSY97). We compare the distributions of the index and its components, as well as the relationships between the components in two countries with contrasting institutional arrangements. We also test for construct validity by assessing the statistical association between CNPI and country-specific measures which are considered good indicators of low-quality employment, and discuss the possible effects of methodological differences between the surveys on the index values. The fifth section concludes.

2 Employment precarity: definition and measurement

2.1 The multidimensionality and comparability of precarious work: conceptual and methodological issues

Precarious employment is usually understood as "uncertain, unpredictable, and risky from the point of view of the worker" (Kalleberg, 2009, p.2). A precarious worker is one who lacks access to stable employment, enabling the development of a social identity and offering legal protection and economic security (Standing, 2011). More systematic attempts to define EP underline the relative and multidimensional nature of this phenomenon (Kreshpaj et al., 2020). Precarity is often conceptualized in terms of deprivation of employee rights, taking as a reference point the guarantees and security associated with the employment relationship defined in a given society as "standard" (Rodgers, 1989, p.1). For example, Kalleberg (2009) associates EP with a lack of employment security, but also diminished opportunities for skill development, uncertain pay, unsafe work, and unavailability of collective voice. Similarly, Vosko (2011, p.2) defines precarious employment as "work for remuneration characterized by uncertainty, low income, and limited social benefits and statutory entitlements".[1]. Others also link EP to

[1]A similar approach is present in the 2017 European Parliament Resolution on working conditions and precarious employment, which describes precarious work as "employment which does not comply with EU, international and national standards and laws and/or does not provide sufficient resources for a decent life or adequate social protection"

uncertainty and instability, low income insufficient to cover one's basic needs, lack of control over the work process, and limited access to regulatory protections and social security (Bosmans et al., 2016; Kreshpaj et al., 2020; Olsthoorn, 2014; Puig-Barrachina et al., 2014; Rodgers, 1989).

Although the idea to capture the complex, multidimensional nature of EP by reference to various employee rights and guarantees of economic security associated with the "standard" employment relationship appears attractive, the usefulness of such definitions for empirical research, especially based on existing quantitative data, is limited. To begin with, the general formulations of employee rights make it difficult (if not impossible) to establish clear and measurable criteria for the assessment of EP. Another problem lies in combining the various aspects of EP into a single measure. The theoretical literature offers no guidance regarding the relative importance of each dimension; apart from a general suggestion that all these various dimensions, somehow need to be taken into account[2]. The difficulties and arbitrariness involved in operationalizing different dimensions and calculating their weights have been acknowledged in the literature, resulting in studies which analyze various aspects of EP[3] independently of each other (Broughton et al., 2016; Frade et al., 2004; Puig-Barrachina et al., 2014). There are also attempts to capture the multidimensionality of EP by using composite indexes. With regard to cross-national comparisons, a recent example is offered by the Employment Precariousness Scale EPRES (Vives et al., 2010), and its slightly modified cross-national version EPRES-E which can be obtained from EWCS data (Padrosa et al., 2021). This measure combines seven dimensions[4]: contract temporariness, disempowerment in the workplace, vulnerability in the workplace, wages, entitlement to workplace rights and social security benefits, ability to exercise workplace rights, and uncertain working times[5]. A limitation of EPRES is that it requires detailed data on working conditions which are not included in regular surveys.

Given these difficulties, a majority of existing cross-country studies of EP use uni-dimensional indicators of either subjective job or labor market insecurity (e.g. Chung & Mau, 2014), or fixed-term employment (e.g. Högberg et al., 2019; Kopycka, 2023; Vossemer et al., 2018). Both types of indicators are readily available in public use data from cross-national surveys such as the European Social Survey (ESS), Labor Force Surveys (LFS), the European Survey of Living Conditions (EU-SILC), or the European Working Conditions Survey (EWCS). Unlike EPRES, they can also be analysed longitudinally, which is important given the considerable variation within fixed-term employment with respect to the situation and career prospects of workers. While some individuals may experience fixed-term jobs as stepping-stones to stable employment, for others such jobs function as "dead-ends" (Booth et al., 2002; Giesecke & Groß, 2003; Kiersztyn, 2016). Consequently, researchers have placed increasing emphasis on longitudinal analyses, driven by the implicit assumption that fixed-term employment is more likely to be associated with EP when experienced in a recurrent way over longer periods of time. In particular, studies have analyzed the occurrence and timing of transitions from fixed-term to permanent employment (Gash, 2008; Högberg et al., 2019; Kiersztyn, 2021), or assessed complete employment trajectories according to the incidence of temporary work and other labor market statuses (Fauser, 2020; Fuller & Stecy-Hildebrandt, 2015; Ritschard et al., 2018; Struffolino, 2019) or temporary work combined with low income (Mattijssen & Pavlopoulos, 2019; Mattijssen et al., 2020).

While we agree that an adequate, cross-national measure of EP needs to take into account the dynamic nature of this phenomenon by focusing on employment careers, we argue that the main weakness of the existing measures stems from their reliance on either survey participants' subjective perceptions of their working conditions or the type of employment relationship or formal contract.

The weakness of subjective indicators of work-related insecurity lies in the fact that they may be shaped by factors other than EP. Risk perceptions are social and cultural constructs, which are dependent on socio-demographic characteristics (Chung & Mau, 2014; Morgenroth et al., 2021), and affected by media reports and opinions about the situation on the labor market in a given country (Kitzinger, 1999; Lübke & Erlinghagen, 2014; Stallings, 1990). Although it has been argued that such perceptions are correlated with objective employment instability and fixed-term employment (Chung & Mau, 2014; Chung & van Oorschot, 2011), it has also been found that many of those who expect their job to end soon are people with regular employment contracts (Fevre,

[2]According to a recent review by Kreshpaj et al. (2020) three dimensions are usually taken into account in definitions and operationalizations of EP: employment insecurity, income inadequacy and lack of employee rights and protection.

[3]Including: the type of contractual relationship, employment duration, working time and schedules, work burden and intensity, pay and salary progression, health and safety conditions, protection against unfair dismissal, discrimination, and unacceptable working practices, as well as access to social security benefits.

[4]Originally the EPRES scale contains six dimensions, but the EPRES-E has one additional dimension: "uncertain working times" added in the cross-national research based on EWCS data. However, data allowing to include the dimensions from original EPRES: "entitlement to workplace rights and social security benefits" was unavailable in EWCS and therefore had to be dropped from the calculations (Padrosa et al., 2021; Vives et al., 2010).

[5]Other composite indexes of EP exist, but are seldom used as they often require conducting special surveys to gather the information necessary to cover all the dimensions of precarity (Lewchuk, 2017), leading to problems with data availability, especially for the purpose of cross-country comparative studies or dynamic analyses.

2007; Mythen, 2005). The latter observation also suggests that in some cases, reference group comparisons may offer more convincing explanations of perceived insecurity than the actual level of EP (Kiersztyn, 2017).

A large body of literature is focused on the type of employment relationship (e.g. Barbieri & Scherer, 2009; Kiersztyn, 2016; Vossemer et al., 2018). Such analyses do not always refer directly to the concept of EP, though their implicit assumption is that non-standard contracts such as fixed-term or temporary work agency employment entail worker exposure to bad working conditions and insecurity (Barbier & Lindley, 2002). This assumption seems warranted in light of studies which mostly confirm that fixed-term workers tend to score lower than their permanently employed counterparts on various objective indicators of employment quality: wages (Kahn, 2016; Kiersztyn, 2016), access to employee benefits (Kalleberg et al., 2000; McGovern et al., 2004), or training opportunities (Arulampalam & Booth, 1998; O'Connell & Byrne, 2012).

Using employment forms as an indicator of EP may be adequate for studies of single-country cases, provided that the corresponding survey items capture important distinctions in the level of worker security and legal protection. However, it remains problematic when used in cross-national comparative analyses, since the actual level of worker protection associated with various types of employment relationships depends on the country-specific institutional and regulatory environment, and cannot be captured in a consistent way by a simple binary indicator of temporary work. The LFS fixed-term employment dummy is a case to the point. In the survey documentation it is described as a "harmonized indicator", referring either to the contractual arrangement (work contract of limited duration) or, alternatively, to the perceived permanency of the employment relationship, whichever is considered more appropriate in a given country. Indeed, information on the type of employment contract does not capture relevant differences in the exposure to EP in countries such as the UK, where the terms and conditions of work are not determined by the type of labor contract, but often specified on an individual basis (McGovern et al., 2004)[6]. However, the subjective indicators used in the UK LFS may also capture regular employees who, for various reasons, think of themselves as "in some way non-permanent", and are subject to the biases of perceived insecurity indicators discussed above (Fevre, 2007). In addition, simple binary fixed-term employment indicators lump together employees who are heterogeneous with respect to the level of precarity they experience (Rodgers, 1989). For example, labor market studies in Germany have generally found that while various kinds of atypical contracts are associated with increased exposure to EP, they are heterogeneous with respect to the level of this exposure (Eichhorst & Tobsch, 2015). Consequently, the common label of temporariness may mask important within- and cross-country differences with respect to working conditions and legal rights of workers, and thus fails to provide a valid criterion for the comparative analysis of EP (Barbier & Lindley, 2002; Rodgers, 1989).

Another problem with fixed-term employment indicators (either those provided in the LFS or in other surveys) is that they cannot be applied to all economically active respondents, as the corresponding survey items are routed to those who define themselves as employees. Recent research has drawn attention to new types of potentially precarious labor arrangements, distinct from hired employment, which have gained in importance due to the rise of the gig economy: platform work, dependent self-employment, and subcontracting (Alberti et al., 2018; Tassinari & Maccarrone, 2020). These phenomena introduce new dimensions of inequality among workers and change the meaning of work as such. In this context, restricting the focus of quantitative EP studies to hired employees becomes an important limitation.

2.2 The proposed operationalization of employment precarity

In the conceptualization of EP proposed in this article, we address the shortcomings of the existing indicators by focusing on the following three types of what we term "adverse experiences":

- *frequent job terminations* reflecting work instability;
- *low earnings from work* to capture the inability to maintain livelihood through the labor market and
- *staying out of work*, which pertains to an individual's participation in the labor force.

We propose to combine these components in an additive manner, as representing distinct sources of precarity. Following existing attempts to construct synthetic measures corresponding to sequence data, we develop an index for comparing the degree of precarity of various employment career sequences in different countries. In order to avoid arbitrary categorizations, this index assigns a numeric value to each sequence, without classifying them as precarious or non-precarious. Under this approach, EP can be considered a phenomenon related to the type of labor contract, but distinct from it. As such, it offers an empirical benchmark to estimate precarity risks associated with different contractual working arrangements in different national contexts.

The choice of the three components is driven by theoretical and practical considerations. From a theoretical point of view, both instability of employment (frequent employer

[6] A similar example is offered by the U.S. indicator of contingent work (Polivka & Nardone, 1989); see description of the U.S. institutional context in section 4.

changes and joblessness) and low earnings, are key defining aspects of EP, commonly included in definitions of precarious work found in the literature (Kreshpaj et al., 2020). While the first two reflect low attachment to the employer and the labor market, they convey an incomplete picture of precarity and need to be supplemented by the low-income measure. This is due to the fact that it is possible to experience frequent job changes combined with high earnings, as illustrated by the concept of "boundaryless" workers (Marler et al., 2002) or "proficians" in Standing (2011) classification. Other elements which are common in definitions of EP, include limited access to legal protection and social security benefits, as well as a lack of collective representation. However, including these dimensions in a cross-country comparative measure is problematic. Perceptions of legal protections are reliant on country-specific standards with regard to the adequate scope of labor regulation. In addition, this item is more likely to be speculative and biased by respondents' knowledge and subjective expectations (e.g., awareness of their employee rights, psychological contracts, organizational culture within the firm, presence of trade unions which may sensitize employees to breaches of the law, etc. Felstiner et al., 1980; Lejeune & Orianne, 2014; Polkowska & Filipek, 2020; Shanahan & Smith, 2021), compared to accounts of actual, basic labor market experiences, such as being in or out of work, or receiving a specific income from a given job. Other dimensions present in definitions of EP, such as control over the work process and other aspects of low job quality, are also difficult to measure without relying on subjective evaluations[7].

The second reason is practical, and driven by our goal of proposing a dynamic measure of EP which can be applied to existing panel datasets over a broad range of countries. While available panel survey data generally include employment history variables allowing to measure the duration and timing of joblessness and job terminations, as well as income from work, detailed items on working conditions and employee rights (such as those used in the EPRES-E) are not commonly found. At the same time, our general framework for the measurement of sequence properties (detailed in section 3) allows for the inclusion of additional indicators of EP in future applications of the CNPI, once the appropriate survey items become available.

While we use the term "adverse experiences" to denote the components of our proposed EP measure, it is important to note that in our conceptualization precarity refers to objective, observable and quantifiable characteristics of careers associated with weak labor market performance: low level of economic activity, instability and low earnings. Precarity as measured by CNPI may not be regarded as an adversity by people whose livelihood is provided for by other means, such as support from other family or household members, and/or public welfare benefits. EP, understood as career instability accompanied by low pay, is conceptually distinct from financial hardship observed at the household level and from subjective perceptions of economic insecurity—although empirically, these phenomena often coexist. We claim that preserving this theoretical distinction is important, as it serves to maintain the clarity of the concepts under study and allows to specify the association patterns between them. In particular, it allows the empirical assessment of important research questions, regarding the socio-economic and institutional characteristics that condition or moderate these associations. One example of such a question concerns ways in which age, gender, social background, household structure and policy context determine whether and to what extent career instability can result in financial hardship.

Another important point is that the CNPI joblessness component is not equivalent to unemployment. For the sake of clarity and simplicity, we focus on a dichotomy of working vs not working, without taking into account job search activities or self-definitions of labor market status. This approach is motivated by the fact that the distinction between unemployment and labor market inactivity can be blurred and is affected by differences between countries, as well as between regions of the same country. For example, in countries with generous and unconditional welfare benefits, as well as in regions with limited opportunities on the local labor market, individuals (especially women) may become discouraged from searching for work and/or report their economic activity status as performing household duties. In such cases, self-defined labor market inactivity may mask a lack of access to acceptable employment, which is a labor market adversity. However, we also acknowledge that in other cases, staying out of work may be a voluntary decision based on individual preferences (e.g., to focus on education or family duties), determined by social background, gendered household constellations and welfare policies present in a given society. The same may be true in the case of low earnings resulting from the choice to work fewer hours. Distinguishing between these situations, differing in their degree of "adversity", would require complex and often arbitrary interpretations of different measures of labor market status among different categories of respondents in different households, countries, regions, and time periods.

To avoid this, we assume that regardless of the reasons for

[7]For example, EPRES includes, one the one hand, subjective evaluations of being respected and treated fairly by the respondents' boss as measures of worker vulnerability. Objective measures of disempowerment at work are also included. However, some of these items, such as "lack of control over working time", may also be regarded as characteristics of secure employment under the Fordist regime, when workers worked regular hours. In fact, the predictability of standard 8-hour shifts may in some cases offer a better work-life balance, compared to contemporary flexible and task-based working time arrangements in professional occupations (see, e.g., Wynn & Rao, 2020).

being out of work or accepting low pay, this status is precarious in that it entails economic dependence—the need to rely on support by others or by state institutions. Our understanding of precarity in terms of low pay and career instability is intended to capture individual economic insecurity generated on the labor market that carries an objective financial risk in case this support is unavailable or withdrawn. The conditions under which this risk is more or less likely to materialise are an issue for empirical research. To account for cross-country and age or gender-related differences in labor market participation in substantive analyses of EP, statistical models using the CNPI should include additional control variables that identify various non-work activities reported by the respondents, such as full-time education, unpaid parental leave, etc. In this context, CNPI can be regarded not as a stand-alone indicator, but as a part of a wider analytical framework designed to study the complex interplay of labor market integration, gender inequality and household dynamics that determine the manifestations and consequences of precarious employment in different countries.

2.3 Sequence-based approaches to the study of labor market disadvantage

Before moving to a more detailed description of the CNPI formula, we provide a brief discussion of sequence-based indices used in analyses of economic and labor market hardship, to which we refer in the selection and measurement of employment sequence properties in each of the three dimensions of EP.

Throughout the years, different approaches to the longitudinal study of workers' economic activity have been developed, reflecting the growing understanding among scholars of the dynamic character of labor market processes, which cannot be adequately studied only from a cross-sectional perspective or from the perspective of single transitions (Aassve et al., 2007). On the one hand, scholars increasingly turn to sequence analysis techniques based on optimal matching algorithms to discover patterns of employment and wage trajectories (Brzinsky-Fay & Solga, 2016; Mattijssen & Pavlopoulos, 2019; Mattijssen et al., 2020). On the other hand, scholars develop composite indices, which are designed to capture multiple characteristics of a sequence in one continuous measure. These indices offer valuable tools to describe and classify various aspects of life course trajectories, but also suffer from several weaknesses when directly applied to the measurement of EP.

In general terms, sequence-based indices can be divided into ones focused on sequence complexity (Billari, 2001; Elzinga, 2010; Elzinga & Liefbroer, 2007; Gabadinho et al., 2011; Ritschard et al., 2018), which focus on state variability within a sequence; and others reflecting sequence quality with respect to elements of a sequence defined as desired/undesired, and their timing (Brzinsky-Fay, 2007; Busetta et al., 2019; Manzoni & Mooi-Reci, 2018). While the first group of approaches has been developed within the theoretical framework of differentiation and individualization of the life-course (Beck & Beck-Gernsheim, 2002), where the objective has been to establish whether modern life histories are becoming increasingly dissimilar and unpredictable (Elzinga & Liefbroer, 2007), the objective of the second kind of sequence-based measures, proposed in the tradition of longitudinal poverty research (for a review see Mendola et al., 2011), has been to capture the long-term economic hardship and/ or accumulation of disadvantage. This research has demonstrated that the incidents of poverty, if episodic, do not necessarily reduce life chances. However, when spells of poverty accumulate they are consequential for subsequent life trajectories (Bane & Ellwood, 1986; Busetta et al., 2019; Duncan, 1984; Mendola et al., 2011; Mood & Jonsson, 2012; Vaalavuo, 2015). It has also been documented that the impact of cumulative poverty is greater for proximate life events than for those in a more distant future—which is interpreted as a recency effect (Mendola & Busetta, 2012).

In the field of labor market disadvantage, sequence-based indices are scarce. Recently, Ritschard et al. (2018) proposed an index designed specifically to measure EP, using a sequence complexity measure based on Shannon's entropy (Shannon, 1948). The entropy of a sequence expresses the variability of states within it as well as the cumulative duration in each state (Billari, 2001). The higher the number of distinct states and the less variance in their length, the higher the entropy. The pure entropy measure does not reflect the recurrence of states, so that a hypothetical sequence *aaabbb* has the same entropy as *ababab*, although the second sequence intuitively appears more volatile/ unstable than the first. In order to account for this difference, Gabadinho et al. (2011) proposed a complexity measure expressed as a geometrical mean of the normalized entropy and the number of transitions normalized by the length of a sequence.[8] However, even after such corrections sequence complexity measures are still problematic as they do not account for ordering of states in terms of their "desirability". Thus, hypothetical sequences of employment (e) and unemployment (u), *eeeuuu* and *uuueee* would be assigned the same complexity value although it is immediately clear that these trajectories are substantively very different. In order to address this shortcoming Ritschard et al. (2018) propose qualifying the complexity measure with a factor depicting the dominant direction of transitions—either a betterment or a deterioration in the

[8] An alternative solution, based on the number of distinct subsequences has been proposed by Elzinga (2010). It accentuates the ordering of states within a sequence to a greater extent than the number of transitions and is therefore ill-suited to distinguish sequences with repeating patterns from their simpler counterparts (*eueueu* produces similar values as *eeeuuu*).

state quality. This solution requires an assumption of a strict order between at least some of the states (for example, that fixed-term employment is more precarious than permanent employment), which leads to the problems of cross-country comparability discussed in section 2.2. In particular, transition costs, understood as distances between states, may differ across countries and across time. Another problem with the correction method proposed by Ritschard et al. (2018) is its specification as a mean difference of negative vs positive transitions over the whole sequence. Consider two sequences of employment and unemployment states: *ueeeeeeeeu* and *ueeuuuuuuu*. Although it is intuitively clear that the first of these sequences is less problematic than the second one, the value of the precarity index is the same, because the correction factor (reflecting the mean direction of transitions), the beginning state and the complexity (reflecting the number of transitions plus the number of distinct states) assume the same value. As revealed by this example, the proposal by Ritschard et al. (2018) does not account for the duration spent in more or less adverse states. The same shortcoming applies to the newly introduced insecurity index (Ritschard, 2021), which is a variation on the precarity index.

Another longitudinal measure of labor market disadvantage is the persistent joblessness index developed by Busetta et al. (2019), following their earlier work on persistent poverty measures (Mendola & Busetta, 2012; Mendola et al., 2011). This index captures the cumulative incidence of joblessness in a sequence so that the higher the incidence of joblessness the higher the index value. However, it attributes a greater value to the occurrence of persistent joblessness, compared to the same amount of time spent out of employment but in several shorter spells. Furthermore, the index takes into account the timing of the experience of joblessness, in line with the idea that the significance of experiencing certain events or conditions may differ depending on their location within a sequence. The persistent joblessness index thus consists of two elements: persistence in unfavorable labor market situations, and recency, reflecting the assumption that the most recent past bears the heaviest on the present (Busetta et al., 2019; Mendola & Busetta, 2012). This measure quantifies, therefore, the severity of longitudinal experience of adversity (in this case joblessness) and is an important contribution to measuring sequence quality. However, as this conceptualization of sequence quality is concentrated on the persistence dimension of experience, it does not capture non-employment spells if they are neither recurrent, nor span two consecutive years, which is an undesired property if a measure is meant to differentiate occupational careers equally well also at lower levels of adversity. Furthermore, this index takes into account only one type of experience and cannot support multidimensional concepts such as precarity, for which staying out of work is but one element, albeit important.

In sum, the propositions discussed above suffer from important deficiencies if applied to the measurement of precarity. The propositions by Busetta et al. (2019) and Mendola and Busetta (2012) capture the experience of either joblessness or poverty, respectively. Sequence complexity measures (Elzinga, 2010; Gabadinho et al., 2011), in turn, do not discriminate between good and bad states, which makes their interpretation with respect to precarity problematic. Attempts to alleviate this problem by Ritschard et al. (2018) led to assumptions of hierarchical order between labor market states, which are problematic in the context of cross-national comparative analyses. Another major weakness of all these conceptualizations is that they do not account for transitions between successive employers, which may not involve a change in labor market status. As far as such cases appear as continuous work in the data, they conceal the instability of the employment relationship, which is one of the key characteristics of precarity. While this is obvious in the case of indices that capture the experiences of adverse states within a sequence, it is also true in the case of complexity-based measures, which, despite their focus on labor market events (transitions), account only for transitions between states, leaving out direct transitions between employers.

Given the doubts associated with using complexity-based indices to conceptualize employment precarity, we develop a multidimensional measure based on sequence quality indicators, and draw on the work by Busetta, Mendola and their co-authors Busetta et al. (2019), Mendola and Busetta (2012), and Mendola et al. (2011) which provides a robust tool to quantify the severity of a longitudinal experience of an adverse condition. We build on their approach to quantify the longitudinal experiences of staying out of employment and not generating sufficient income from work, with an important adjustment allowing us to support the measurement of less persistent occurrences of adversity. Furthermore, we propose an application of their approach to measurement of a longitudinal experience of adverse events, in order to capture the occurrence of job separations in the career sequence. The details of our formula are provided in the next section.

3 The Cross-National Precarity Index

3.1 Calculating the CNPI and its components

In this section, we offer a detailed description of the formula we propose to measure EP. The basic formula for the Cross-National Precarity Index for a sequence S of length T ending in year Y is:

$$\mathrm{CNPI}^{S(T,Y)} = \beta \cdot \mathrm{AE}_{\mathrm{jobtrm}}^{S(T,Y)} + \gamma \cdot \mathrm{AE}_{\mathrm{nonwrk}}^{S(T,Y)} + \delta \cdot \mathrm{AE}_{\mathrm{earnlo}}^{S(T,Y)} \quad (1)$$

with

$$\beta + \gamma + \delta = 1$$
$$\beta, \gamma, \delta > 0 \quad ,$$

where $\mathrm{CNPI}^{S(T,Y)}$ is the value for a sequence S of length T ending in year Y, $\mathrm{AE}^{S(T,Y)}_{\mathrm{jobtrm}}$ is the severity of adverse experience: job terminations, $\mathrm{AE}^{S(T,Y)}_{\mathrm{nonwrk}}$ is the severity of adverse experience: non-work, $\mathrm{AE}^{S(T,Y)}_{\mathrm{earnlo}}$ is the severity of adverse experience: low earnings, and β, γ, δ are weights.

A linear combination of components allows for attaching a weight to each of them. Depending on the research question and the way the CNPI will be used in specific empirical analysis, it may be reasonable to stress particular components at the expense of others by differentiating the weights.

We define longitudinal severity of an adverse experience (AE) as a weighted mean of two elements representing: a) the persistence of experiencing adversity throughout the whole sequence; and b) the temporal proximity of the adverse experience to the last time unit of the sequence (recency) multiplied by its intensity.

$$\mathrm{AE}^{S(T,Y)} = \alpha \frac{\sum_{i,j \in S^{(T,Y)}} d_{\mathrm{ji}}^{-1}}{\sum_{k=1}^{T-1} \frac{k}{T-k}} + (1-\alpha) \frac{\sum_{j \in S^{(T,Y)}} j \cdot I_j}{\frac{T(T+1)}{2}}; \quad 0 \le \alpha \le 1, \tag{2}$$

where $\mathrm{AE}^{S(T,Y)}$ is the severity of adverse experience for a sequence S of length T ending in year Y, α is the weight attached to persistence of adverse experience, d is the distance between time units j and i with a non-zero value of adverse experience, i, j are the position indexes of time units in an ordered sequence, and I_j is the intensity of an adverse experience in year j.

The first addend in the equation represents the persistence of the adverse experience throughout the sequence. The basic metric are distances, denoted in the formula by the letter d with a subscript ji, between any pair of time units i and j which belong to an ordered sequence S and in which an individual experiences adversity. Imagine an ordered sequence of five consecutive years, in which year 1, year 3 and year 5 of the sequence are affected by an adverse experience ($S = 10101$). This yields three pairs of years: 1–3, 1–5 and 3–5. The distances are 2, 4 and 2, respectively. The sum of the inverses of these distances $(1/2 + 1/4 + 1/2)$ expresses the temporal proximity of adverse experiences throughout the sequence. In order to normalize the measure to the range $[0, 1]$, the numerator is divided by its theoretical maximum, which is reached when adversity occurs every year. For the application to empirical data it is necessary to specify the classification of time units as being characterized by an adverse experience or not. The classification method depends on the type of the experience in question and users are free to decide on the differentiating criterion. For the purpose of the operationalization of EP we define a year as affected by non-employment if a person stays out of work for at least one month in this year. We define a year as affected by low earnings if an individual reports their personal total yearly earnings to be lower than a set threshold. We define a year as affected by job terminations if a person reports having exited at least one job in this year.

It is important to note that the persistence measure captures the longitudinal severity of an adverse experience only partially, as it does not account for the intensity of this experience within a single time unit and is indifferent to the positioning of the occurrence pattern with respect to the direction of the sequence. To illustrate, consider two sequences which are mirror images: $S_1 = 01011$ and $S_2 = 11010$. In case of the first sequence, adverse experiences start in year 2, and cumulate in the last years of the sequence. In contrast, the second sequence starts with adverse experiences, which are no longer present in the last year. s_2 can be interpreted as a stepping-stone trajectory, and, as a whole, is less precarious compared to S_1. However, both these sequences are identical with respect to the persistence of the adverse experience. Therefore, we complement the longitudinal severity measure by including further sequence properties, which is achieved through the second addend in the formula.

The second addend captures the recency and intensity of the adverse experience. The numerator is a sum of products of position indexes j of time units within the sequence and the intensity of the adverse experience in that time unit (I_j). Intensity is defined in a 0–1 bound, where 0 means that the time unit has not been classified as affected by the adverse experience. The denominator represents the theoretical maximum of the expression in the numerator, achieved when each time unit of a sequence is affected by an adverse condition to a maximum extent. To illustrate, imagine a sequence of five years with different intensities of an AE: S = 1|0|0.5|0.7|0.3. The numerator equals

$$1 \cdot 1 + 0 \cdot 2 + 0.5 \cdot 3 + 0.7 \cdot 4 + 0.3 \cdot 5 = 6.8$$

and the whole expression amounts to $\frac{6.8}{1+2+3+4+5} = 0.45$. Just as with classifying time units as affected or not by an adverse experience, defining the intensity parameter I is up to the researcher. We define the intensity of non-employment (I_{nonwrk}) to be the fraction of a time unit (year) spent out of employment. The intensity of low-earnings experience (I_{earnlo}) is defined as the relative distance of total yearly earnings from a selected low-yearly-earnings threshold. This parameter equals 0 for earnings above the threshold, and 1 minus the proportion of the threshold earned by an individual in a given year for earnings below the threshold. The maximum value of 1 is reached when a person does not report any earnings for a given year. We define the intensity of job termination experience (I_{jobtrm}) as the number of job terminations in a given year divided by a threshold value $\max_{\mathrm{jobtrm}}$, with a cap value of 1, which is the maximum intensity. Setting a threshold for the number of job terminations expresses the intuition that increases in the number of such adverse events do not change the severity of the experience after a certain "saturation point" has been reached. The specific value of $\max_{\mathrm{jobtrm}}$ may vary with respect to the nature of the event and can be set either through theoretical consideration or in accordance with average frequencies observed in the population under study. The three intensity parameters in the formal notation are presented below.

$$I_{\text{jobtrm}} = \begin{cases} \frac{n_{\text{jobtrm}}}{\max_{\text{jobtrm}}} & \text{if } n_{\text{jobtrm}} \leq \max_{\text{jobtrm}} \\ 1 & \text{if } n_{\text{jobtrm}} > \max_{\text{jobtrm}} \end{cases} \tag{3}$$

where n_{jobtrm} is the number of job terminations experienced by an individual in a given year, and $\max_{\text{jobtrm}}$is the severity threshold.

$$I_{\text{nonwrk}} = \frac{\text{mths}_{\text{nonwrk}}}{12}, \tag{4}$$

where: $\text{mths}_{\text{nonwrk}}$ is the number of months out of employment of an individual in a given year.

$$I_{\text{earnlo}} = 1 - \frac{\text{earn}}{\text{earnlo}}, \tag{5}$$

where earn is the yearly individual earnings, and earnlo is the low earnings threshold.

Lastly, the weighting factor α represents the importance of the persistence versus recency-intensity properties for the overall longitudinal severity measure. Ultimately, it is up to the researcher to define α for their specific research question and for each adverse experience type.

3.2 Putting the index to work: Example sequences

For the purpose of assessing the performance of CNPI we have created hypothetical sequences of employment careers. Examining these ideal-typical representations provides a better picture of how well the index captures the adverse experiences associated with EP, given the diversity of employment patterns. Figure 1 presents 15 example 5-year sequences and the corresponding values of the composite index and its components, capturing the adverse conditions of low income (AE_{earnlo}) and non-employment (AE_{nonwrk}), and the adverse events of job terminations (AE_{jobtrm}). In the basic conceptualization proposed here we treat each CNPI component as equally important, thus the weights β, γ, δ are all set to the value of 1/3. We also apply equal weights (α=0.5) to both addends of each component. The ceiling number of job terminations per year ($\max_{\text{jobtrm}}$) is set to 3, based on the assumption that careers in which each job lasts for a maximum of 4 months on average are characterised by a high degree of instability. The low-yearly-earnings threshold equals 50% of the gross average monthly earnings of dependent employees multiplied by 12. The sequences are presented in ascending order of the CNPI value.

The least precarious career pattern, with a zero CNPI value, is a sequence consisting solely of continuous work for a single employer (or stable self-employment), with yearly earnings above the low-earnings threshold. Turning to sequence 2, we can see how the index reacts to the inclusion of a period of 9 months out of work in year 4. Such a pattern may for instance pertain to a young professional who enjoys stable, well-paid employment, but in case of a job termination needs a longer search period to find an adequate position. We then experiment with moving the unemployment phase back (Seq 3) and forward (Seq 4) by a couple of months, confirming that the index behaves in the desired way. First, the values barely change, because indeed, situations are very similar. Second, if the non-employment spell stretches over two years, the index value increases because the persistence dimension is elevated. This is to some extent compensated for by the reduction in the severity of the low-earnings condition, as short non-employment in year 3 (in case of sequence 3) or year 5 (in case of sequence 4) is not sufficient to bring yearly earnings for that year below the selected threshold, whereas the relative distance to the threshold in year 4 is reduced. The highest index value of sequence 4, compared to sequences 2 and 3, results from the fact that the non-employment experience is the most recent in this case. This recency increases the non-employment severity measure as well as the job termination measure.

Sequences 5 and 6 represent employment patterns which are characterized by continuous employment, though not generating enough earnings to keep individuals above the low-earnings threshold. This may pertain to very low-paying jobs, but especially to situations of underemployment by low hours. By comparing sequence 5 and 6 we can observe how employer changes increase the CNPI value. Sequence 7, when compared to sequence 5, illustrates the effect of non-employment in the last year of the sequence. This generates higher values on the severity of low earnings, non-employment as well as job terminations.

A comparison of sequences 7 and 9 shows that more non-employment later in the sequence significantly raises the index value. Moreover, it is notable that the moderation effect of early stable and well-paid employment is limited—in the end sequence 9 scores higher on CNPI than sequence 7. Sequences 8 and 12 can be described as discontinuous but with differing severity of adverse experiences. Sequence 12, with earnings falling more strongly below the low-earnings threshold, less time spent in employment and more frequent job terminations, receives a higher CNPI value, compared to sequence 8.

Lastly, sequences 10 and 11 provide an illustration of how discontinuous employment increases the CNPI measure. Although the non-employment component is lower for sequence 11, the job termination component is substantially elevated, which increases the value of precarity. By comparing these two example sequences we can observe, further, how the persistence dimension affects the value of the CNPI components. Despite the fact that the overall time in employment for sequence 10 is higher, it receives a higher value of AE^{nw} because non-employment is experienced in each year.

	Year 1: job sequence low earnings (w1)	**Year 2:** job sequence low earnings (w2)	**Year 3:** job sequence low earnings (w3)	**Year 4:** job sequence low earnings (w4)	**Year 5:** job sequence low earnings (w5)	CNPI	AE_{earnlo}	AE_{nonwrk}	AE_{jobtrm}
1	* * * * * * * * * * * * 0.00	* * * * * * * * * * * * 0.00	* * * * * * * * * * * * 0.00	* * * * * * * * * * * * 0.00	* * * * * * * * * * * * 0.00	0.00	0.00	0.00	0.00
2	* * * * * * * * * * * * 0.00	* * * * * * * * * * * * 0.00	* * * * * * * * * * * T 0.00	* * * 0.50	* * * * * * * * * * * * 0.00	0.07	0.07	0.10	0.04
3	* * * * * * * * * * * * 0.00	* * * * * * * * * * * * 0.00	* * * * * * * * * T 0.00	* * * * * 0.17	* * * * * * * * * * * * 0.00	0.08	0.02	0.17	0.03
4	* * * * * * * * * * * * 0.00	* * * * * * * * * * * * 0.00	* * * * * * * * * * * * 0.00	* * * * T 0.17	* * * * * * * * * * 0.00	0.82	0.02	0.18	0.04
5	* T * * * * * * * * * * 0.2	* * * * * * * * * * * * 0.25	* * * * * * * * * * * * 0.25	* * * * * * * * * * * * 0.25	* * * * * * * * * * * * 0.25	0.21	0.62	0.00	0.01
6	* * * * * * * * 0.50	* * * * * * * T * * * T 0.20	* * * * * * * * * * * * 0.50	* * * * * T * * * * * * 0.25	* * * * * * * * * * * * 0.10	0.28	0.63	0.01	0.22
7	* * * * T * * * * * * * 0.20	* * * * * * * * * * * * 0.25	* * * * * * * * * * * * 0.25	* * * * * * * * * * * * 0.25	* T 0.80	0.31	0.72	0.14	0.09
8	* * * * * T 0.50	* * * * * T * * 0.20	* * * * * * * * * T 0.00	* * * * * * * * 0.00	* * * T * * * * * * 0.20	0.35	0.18	0.63	0.25
9	* * * * * * * * * * * * 0.00	* * * * * * * * * * * * 0.00	* * T 0.60	1	1	0.38	0.55	0.57	0.03
10	* * * * * T * * * * * 0.00	* * * * T * * * * * * 0.10	* * * * T * * * * * * 0.00	* * * T * * 0.4	* * * * T * * * * * * 0.00	0.45	0.10	0.60	0.67
11	* * * * * * * * * * * T 0.00	* * * * * * * T 0.30	* * * * * T * * 0.30	* * T * T * T * 0.00	* T T * * * * 0.00	0.48	0.13	0.51	0.81
12	* * * * * * * T 0.00	T * * * * T 0.20	* * * * T 0.40	* * * * * * T 0.20	* * T 0.60	0.66	0.51	0.78	0.69
13	* T 0.70	* T 0.70	* T 0.70	* * * * * * * T 0.50	* * * * * * * * * T 0.40	0.72	0.77	0.74	0.67
14	* T 0.90	* * T 0.80	* T 0.90	* * * T 0.80	* T 0.90	0.82	0.93	0.88	0.67
15	T T T 0.94	T T T 0.94	T T T 0.94	T T T 0.94	T T T 0.94	0.93	0.97	0.88	1.00

Figure 1

*Example sequences and values of CNPI and its components. For each year of each sequence, the upper row depicts employment and the occurrence of job terminations in successive months, where * refers to month in employment, and T to month in employment followed by job termination or a job lasting only one month. Below the monthly statuses, low earnings intensity is provided for each year. Low earnings intensity values are highlighted for years in which the adverse experience occurs. Values ≥ 0.5 are marked with a darker shade.*

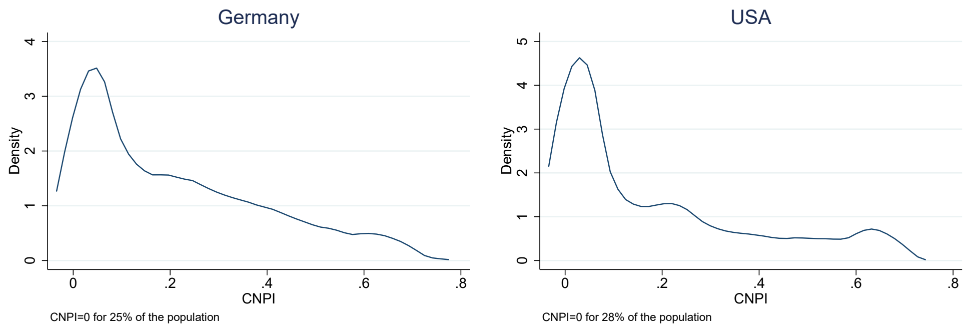


Figure 2

Distribution of CNPI in Germany and the USA. Data on 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence and CNPI values above zero. Source: SOEP data for the years 2009–2017 (waves 2009–2018), and NLSY97 data for 2013–2017 (waves 2013–2019). Weighted sample: N = 3709 (2939) in Germany and 4630 (3434) in the U.S.

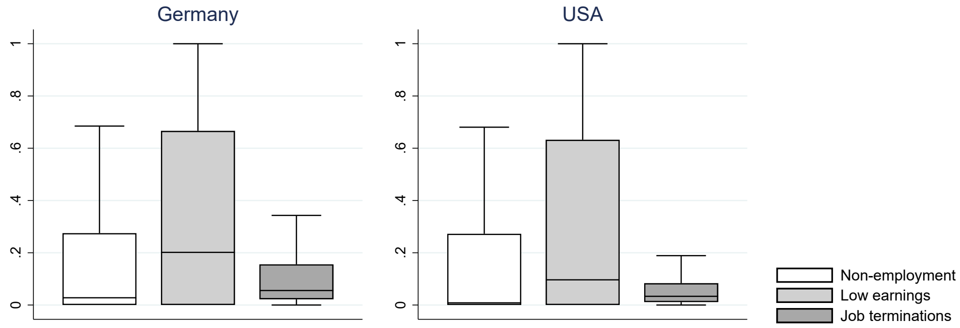


Figure 3

Distribution of CNPI components in Germany and the USA. Data on 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence and CNPI values above zero. Source: SOEP data for the years 2009–2017 (waves 2009–2018), and NLSY97 data for 2013–2017 (waves 2013–2019). Weighted sample: N = 2939 *in Germany and 3434 in the U.S. Outliers are excluded.*

The low earnings component, in turn, is higher in case of sequence 11 despite a better income situation in two last years, which is a result of experiencing low earnings for two consecutive years early on. The importance of the recency of adverse experiences is noticeable when comparing the two most precarious sequences 13 and 14. It stands out how much the CNPI measure decreases when a recovery phase follows a period of severely precarious labor market presence. The last sequence illustrates a situation for which the index reaches its (almost) maximum value. It maximizes the joint value for non-employment and job terminations, which occurs when an individual has three separate monthly employment spells each year. For the illustration we assumed work intensity of 10 hours a week and hourly pay at the level of 50 percent of average gross hourly pay (which is approximately the minimum wage level in Germany). Upon reducing work intensity to 1 hour per week (which is the minimum according to the ILO definition of employment), while keeping the wage level constant, the CNPI value increases slightly to 0.95.

4 Empirical application: Germany and the U.S.

Empirical application of CNPI is conducted on data on individual employment biographies in Germany and the United States. These two countries represent contrasting institutional environments, described in theories of the welfare state, production, employment and industrial relations regimes (Esping-Andersen, 1990; Hall & Soskice, 2001; Visser, 2009), shaping the incidence and manifestations of labor market precarity. Germany is characterized as a coordinated market economy, with high levels of employment protection especially for insider jobs with regular employment contracts. The U.S. is a liberal market economy, with high worker mobility and lower levels of legal employment protection (Kalleberg, 2009). The institutional conditions present in both countries are reflected in the way labor market hardship is studied.

In Germany, studies of precarious work focus on non-standard employment arrangements, in particular, fixed-term labor contracts (*befristeter Arbeitsvertrag*); temporary agency work and marginal forms of part-time employment with a specified wage ceiling: mini/midi jobs (Keller & Seifert, 2013; Weinkopf, 2009). While labor market studies in Germany have generally found that such contracts are associated with increased exposure to employment precarity, they are heterogeneous with respect to the level of this exposure (Eichhorst & Tobsch, 2015).

In the U.S., the standardized regulation of employment contracts is very limited, and many companies avoid entering into any sort of contract with their employees. Without a contract, the law defines the employment relationship as "at will", rendering the concept of fixed-term employment largely meaningless. While the labor market literature does point to certain so-called alternative work arrangements (on-call/ day labor, temporary help agency work) or contingent work (jobs perceived as temporary and not expected to continue for non-personal reasons) which may be associated with increased exposure to precarity (Abraham & Houseman, 2020; Polivka & Nardone, 1989), the incidence of such jobs is very low. In 2017, temporary agency work and on-call labor accounted for roughly 2.6% of the working population, and contingent employment—less than 4% (Abraham & Houseman, 2020). Hence, studies of labor market hardship in the U.S. focus on rewards and career outcomes associated with work: low pay and lack of access to basic employee benefits such as health insurance, retirement plans, or paid leave, are deemed characteristic of "bad jobs" (e.g.

Kalleberg et al., 2000).

In light of these differences, Germany and the U.S. offer a good illustration of our points regarding the limitations of using the fixed-term employment indicator as a cross-nationally comparable measure of precarity. At the same time, given the differences in the labor market regimes in both countries, they allow us to evaluate the performance of the CNPI across a broad range of institutional settings.

4.1 Data and methods

We use data from the German Socio-Economic Panel (G-SOEP) (Study, 2019) and the National Longitudinal Survey of Youth 1997 Cohort (NLSY97) (Center for Human Resource Research (CHRR), 2021). Both are long-standing nationally representative surveys that cover a wide range of variables regarding the respondents' work activity. The data allow for a reconstruction of monthly work histories and the number of employer separations, and offer regular measurement of income from work. However, the surveys differ in their methodologies. The G-SOEP is a household survey conducted on an annual basis; all members of the sample households aged 18 or above in the year of the survey complete the adult questionnaire. NLSY97 includes five one-year cohorts of young Americans, born between 1980 and 1984. The survey waves were fielded annually between 1997 and 2011, and biannually henceforth. At the time the most recent available data was collected, in 2019, respondents were between 35 and 39 years old. In each round of data collection, participants were asked retrospective questions regarding each job they had done since their previous participation in the survey.

We analyze employment sequences lasting five consecutive calendar years for individuals aged 33 to 37 in the last year of the sequence, who reported working for at least one month during the sequence. While the general formulation of the CNPI allows for the study of sequences differing in length, depending on data availability and the particular research question to be examined, five years is sufficiently long to capture the dynamics of individual employment trajectories. However, we also conducted additional analyses for the G-SOEP using ten-year sequences and found consistent results (available upon request from the authors). The age restriction is to allow for comparability between the surveys—the age brackets match those for the U.S. cohort sample in 2017, the most recent year of non-censored observations for both countries. To address the small sample size in Germany after applying this restriction, we pooled all five-year sequences starting from 2009 and ending in 2017 (i.e., we take into account five overlapping periods: 2009–2013, 2010–2014, 2011–2015, 2012–2016, and 2013–2017). In order to account for the resulting clustering, in the inferential analysis we calculate robust standard errors. For the U.S., we only take into account sequences covering the most recent period, 2013–2017 (given the cohort design of the NLSY97, pooling overlapping sequences would result in an overrepresentation of sequences experienced at a younger age). The final sample sizes were 3709 for Germany, and 4630 for the U.S. Both samples were weighted using cross-sectional weights created by the data providers for the last year of observation[9].

Calculating the components of the CNPI requires specific decisions with regard to the measurement of work status, defining what constitutes a job termination, and determining the threshold number of job terminations per year (max_{jobtrm} in Formula 3), as well as the low earnings criterion[10]. These decisions need to be adapted to the methodological approaches to career reconstruction taken in national surveys. In G-SOEP, work status is self-defined and collected using calendar questions (i.e., the respondents are asked about their labor market status in each month of each year; different statuses can coincide). All months in which the respondents have reported doing any work are treated as spent on work, regardless of other activities (including unemployment) reported in that same month. The NLSY97 collects information about the start and end dates of each job held by the respondents (with no restrictions with regard to the maximum number of jobs to be reported) and about all breaks within each job lasting one week or longer (not counting paid vacation or paid sick leave) as well as their reasons. This level of detail could lead to an underestimation of the number of months spent in employment, should all the job gaps be counted as periods of joblessness. To avoid such biases, we assign working status to all months during which the respondents had reported working (in any kind of job, including active military duty; for a rationale see,

[9]For Germany we apply the cross-sectional weights available in the dataset. For the U.S. we use custom weights calculated by the online tool provided by data distributors (available at: https://www.nlsinfo.org/weights/nlsy97), adjusted to not affect the total size of the weighted sample. The clustering solution is obtained for unweighted data, but data for the U.S. are restricted to the nationally representative general population sample of the 1980–1984 birth cohorts (we drop the overrepresentation of ethnic minorities included in the study); $N = 3505$. For the analyses presented in Figures 6, 7, 8 and 9 the last year of observation pertains to the dependent variable. For all the remaining analyses, it is the last year of the sequence.

[10]Alternative approaches with regard to the measurement of low pay, job terminations, or joblessness are possible. For example, scholars may use net rather than gross earnings, as well as different low pay thresholds. Developing alternative specifications may be necessary in order to include other national panel surveys. For example, the current specification of the number of job terminations in the CNPI takes into account all the jobs held by the respondents (also including secondary jobs). Some surveys, like the UK Household Longitudinal Survey, only collect retrospective information on the main job and would therefore require an alternative operationalization.

e.g., Kleykamp, 2007) for 2 or more weeks; all the remaining months are classified as joblessness. For both countries, all periods of paid leave (including parental leave) are treated as work. A comparison of Germany and the U.S. with respect to the distribution of the number of months in employment in each sequence, reported in the appendix, Table A1, suggests that there are no major differences between the two countries.

With regard to job separations (understood as terminating the relationship with a specific employer), for Germany we combine information from two sources: the calendar data on labor market activity in the year prior to the survey year and the direct question about job terminations in the current or previous year. On the basis of calendar data we count the number of employment spells (full-time, part-time, marginal employment and furlough) ending in a given year (furlough does not end part-time or full-time employment, but prolongs them). Furthermore, if a respondent reports a job termination directly, but no job spell ends in the calendar data, the number of job terminations is set to 1. For the U.S., we take into account information on the end dates of each job[11], as well as the start of within-job gaps lasting for at least 5 weeks (in case of gaps for reasons related to job characteristics or economic conditions, such as difficulties within the firm, lack of work due to seasonality of the job, or quitting a job) or at least 6 months (in case of gaps for personal reasons, e.g., unpaid leave, army service, health problems, pregnancy or childcare, or other family reasons)[12]. A descriptive analysis of the distribution of the total number of job terminations according to the above definitions in each five year sequence (Figure B1 in the appendix) points to higher maximum values of the number of such events in the U.S., which is to be expected in a liberal market economy. However, the average number of job terminations over 5 years is lower in the U.S. compared to Germany (Table A2). The yearly number of job terminations observed in both countries extremely rarely exceeds 2 (Table A3), we therefore adopt the same value 3 for the maximum intensity of the adverse event experience for the purpose of this empirical application, as we did in section 3.2.

For the calculation of the low earnings component, we take into account the total annual gross (before tax) income from work earned by the respondents. The choice of gross rather than net earnings is due to the fact that this is the only measure provided in the NLSY97 data. In the G-SOEP, both earnings measures are available. However, gross earnings in the German case are a more comprehensive indicator of job quality, as they include social insurance contributions. This means that two individuals with the same net wage may differ in terms of access to important work-related benefits such as unemployment benefits and pensions. In Germany, the total gross earnings are reported directly for the calendar year preceding the survey wave. In the U.S., annual earnings data is collected once every two years (and less frequently for those who drop out and re-enter the sample), so to calculate total earnings, we used information on the total hourly remuneration (including basic pay and any additional bonuses, such as tips, commissions, or overtime) from each job, measured at the time of the survey (for ongoing jobs) or at the time the job ended. Given that for a majority of the respondents wages are measured at least once every two years since 2011, we do not expect the estimations to be significantly biased by changes in wages while working for the same employer. The annual earned income from each job is obtained by multiplying the total number of weeks worked in this job throughout the year (within-job gaps lasting up to 1 week are treated as continuous work), the average number of hours per week, and the hourly wage rate. For each year, we then calculate the total earnings for all jobs (with the exception of military jobs for which specific wage information is unavailable)[13]. The low-earnings threshold is 50% of the average annual gross earnings for full time employees in a given year expressed in national currency for each country reported in the official data[14]. In the appendix, we provide additional information comparing the two countries with respect to the distribution of the number of years with earnings below the low-earnings threshold in each five-year sequence (Figure B2), and the distribution of the distance between the annual gross wage and the threshold (Figure B3 and Table A4).

The analyses proceed as follows. First, we describe the distribution of the CNPI and its components, to investigate the multidimensional structure of the index. Using cluster and correlation analysis, we examine the relationships between the components of the index and assess how each of them contribute to the overall value of the CNPI in each country. We demonstrate that job terminations, staying out of employment and earning little income form separate sources of precarity and can be empirically found in different combinations, not least reflecting differences in the country's legal and cultural context. In this part of the analysis, we adopt equal weights for all the components of CNPI, as well as for

[11] Jobs reported as ongoing during a given wave but no longer mentioned in the subsequent wave are also treated as terminated in the month following the first wave; in other cases right censoring is not counted as a job termination.

[12] While the choice of these criteria is to some extent arbitrary, an examination of the duration of job gaps reported by the respondents shows that a majority of them last only up to 4 weeks, after which the respondents resume their interrupted jobs. Gaps this short are unlikely to result from job terminations.

[13] If the respondent has a military job in a given year, and the sum of total yearly earnings from all other jobs is below the low-earnings threshold, this is treated as a missing data case. The number of cases lost due to the lack of data on military wages is negligible.

[14] Source: for the U.S, OECD wage statistics, downloadable from https://stats.oecd.org/viewhtml.aspx?datasetcode=AV_AN_WAGE&lang=en; for Germany, German Statistical Office: https://www.destatis.de/DE/Themen/Arbeit/Verdienste/Verdienste-Branche-Berufe/_inhalt.html#_6hg8st4rt.

their two dimensions: persistence and recency-intensity.

Second, we address the issue of weighting parameters present in the formula of the index. We show how the values of the index and its components change through the application of different weights and we estimate the correlation between alternative specifications to assess the robustness of the measure.

Third, we investigate the criterion validity of the CNPI. We assess whether the observed values of CNPI in both countries behave according to theoretical expectations by testing its association with country-specific "benchmarks"—indicators used to capture EP, measured at the beginning and after the end of the sequence. In Germany, labor market precarity is well-captured by temporary employment, which—in the most negative scenario—is also associated with higher unemployment and job churning risks. Accordingly, the benchmark for Germany distinguishes between three statuses observed at the time of the survey in a given year, ranging from the most to the least precarious: not working, working on a fixed-term contract, and working on a permanent contract. We disregard the self-employed as they constitute a small residual category of workers in Germany. For the U.S., we use access to employer-provided benefits as a differentiating factor for the labor market situation. We take into account three types of benefits, which are the most common and mirror the basic benefits to which regular employees in Europe are entitled: health insurance, pension plans, and paid leave: either sick leave or vacation (see also Kalleberg et al., 2000). Since the NLSY97 includes retrospective dummies to capture the availability of employee benefits offered in each job, we adopt a yearly measure, in which a given benefit is defined as present when it is available for at least 9 months of the year (from any job the respondents held in a given month; individuals out of work are coded as having no benefits). The final benchmark variable distinguishes three types of situations: lack of coverage by any of the three benefits, coverage by one or two benefits, and full coverage: by all three benefits[15].

To test the association between CNPI and the two country-specific benchmarks measured after the end of the sequence, we use multinomial logistic regression models, controlling for basic socio-demographic characteristics (the level of education, marital status, age and gender, as well as race for the USA). The dependent variables are: employment status observed in the survey wave in the year directly following the sequence (Germany; G-SOEP waves 2014–2018) and access to benefits observed in 2018 (USA). We also examine the association between the labor market situation/access to benefits in the first year of each 5-year sequence (waves 2009–2013 of the G-SOEP in Germany, year 2013 for the NLSY97) and the CNPI value for this sequence. We perform OLS regression analysis, predicting the level of CNPI in the three groups distinguished by the benchmark variables in year 1, conditional on the basic demographic characteristics listed above. Descriptive statistics for the variables in these models are provided in the appendix (Tables A5 to A8).

In a final analysis, we apply a different approach to testing the validity of CNPI, by investigating the life-course dynamics of the index and its components in both countries. It is generally believed that labor market hardship concentrates in vulnerable groups of workers, which is youth but also older workers, due to health deterioration and skill obsolescence in a rapidly changing economy (Picchio, 2021). Therefore, we expect to find a u-shaped pattern of precarity levels across the life course. To assess whether the changes in average CNPI values across the life course are consistent with theoretical expectations, we drop the age restriction applied in the earlier analyses, and include in the sample all overlapping five-year sequences starting between 2003 and 2013. Specifically, earliest sequences are from the years 2003–2007, and the most recent cover the period 2013–2017. Calculations were made for people aged 25–67 (Germany) and 25–37 (the U.S.) at the end of the sequence (sample sizes were 71756 and 55809 respectively). Due to the cohort design of the NLSY97 study, data on employment sequences experienced by older cohorts is not available.

4.2 CNPI and its components: distributions and associations

In Figure 2, we assess the distributions of CNPI in each country. In order to get a more differentiated picture, the graphs exclude individuals with zero precarity index values (which make up 25% and 28% of the subpopulation of interest in Germany and the U.S., respectively). In both cases, the distribution is right-skewed, indicating the low prevalence of EP. This is to be expected given that the age categories used for the analysis include individuals who are already more or less established on the labor market before we start observing their careers. Substantial labor market hardship is a marginal phenomenon among prime-age individuals; the employment rates for this age category are among the highest in developed economies (OECD, 2023). We find higher precarity levels in Germany than in the United States. The distribution in the U.S. is steeper and CNPI values are more strongly concentrated at very low levels.

With regard to the distributions of the CNPI components, non-employment is characterized by a relatively wide range of values in both countries (Table 3). The median value is very low, and about three-quarters of the population under study experience no or almost no non-employment. The values for job separations are low in both countries, mostly

[15] To test the robustness of our results, we also used an alternative indicator of benefit coverage, replacing the 9 out of 12 months criterion by one which assumes coverage if a benefit is present in at least one of the first two months of each year, and found that the choice of the indicator does not affect the findings.

falling below 0.2. The tail is longer in case of Germany, indicating more differentiated experience, and in the U.S. the values of this component are visibly lower. Similarly, the low earnings component reaches somewhat higher values for a larger percentage of the weighted sample in Germany, compared to the U.S. In fact, a majority of the U.S. sample scores below 0.2 on this component, but in both countries the distribution is flatter than in the case of the other adversities, especially job terminations. The differences between the countries with regard to the CNPI components can be to some extent caused by differences in survey methodologies and the annual earnings measures (see section 4.1 for details); we return to this issue in the discussion.

We confirm the relevance of the three aspects of precarity that are the focus of our study by analyzing the relationships between the three components of the CNPI. Table 1 presents correlation matrices of the 5-year index components and the composite index for Germany and the U.S. We see that longitudinal job instability is to a high degree independent of experiencing low earnings from work and non-employment in both countries, and that the latter two items are also the main drivers of the composite index values. However, Table 1 also points to high correlations between the low earnings and non-employment component values, raising the question of their reducibility. To further explore the relationships between the index components, while shedding more light on the issue of analytical distinctiveness of joblessness and low earnings, we apply cluster analysis on the three components of the index as clustering variables. Prior to the clustering the components have been standardized in order to correct for their unequal distributions and mean values. We apply hierarchical clustering with Ward's linkage. Figure 4 shows the cluster composition with respect to non-employment, low earnings and job terminations. The component values in the figure represent the original (non-standardized) values. Furthermore, we report the values of the overall index, with different specifications of weights for each component: the first using equal weights for each of the three components, and an alternative specification using a different set of weights (see section 4.3 for details). The preferred solution for both Germany and the U.S. contains 5 clusters.

In both countries we find the largest, non-precarious stable employment cluster, which is characterized by very low values on all three adversity components and low values of the composite index. Furthermore, both clustering solutions contain an inactivity cluster, which is defined by high levels of longitudinal non-employment and low earnings occurrence combined with infrequent job terminations. Careers in this cluster involve long employment breaks after initial job activity and are more often found in Germany. Another cluster occurring, though to a different extent, in both countries is the job mobility cluster, for which a slightly elevated level of job terminations component is discriminatory. This cluster includes careers where the relatively high exposure to job terminations is accompanied by low to moderate values of the non-employment and low income components, resulting in a low level of precarity.

The analysis has also identified country-specific clusters. In Germany we find a low work intensity segment with a moderate level of overall precarity, characterized by stable employment but low earnings from work. This cluster pertains possibly to secondary earner careers, in which casual forms of employment, such as Mini-jobs are more common (Konle-Seidl, 2021). The second cluster typical for Germany is the job churning cluster, which combines high job-exit mobility with low earnings experiences and only slightly elevated non-employment component values. These employment careers may involve unstable short-lived and relatively low paying jobs with relatively short unemployment spells between them. While they are relatively rare in terms of occurrence, they are similar to the inactivity cluster in terms of overall precarity. Specific for the U.S. is the job instability cluster, which is somewhat similar to the German job churning cluster in that it is associated with the highest exposure to job terminations, but much more heterogenous with respect to the other two precarity components. In this cluster, jobs can be either good or bad in terms of pay, but are relatively short-lived. Lastly, the job discontinuity cluster involves high exposure to low earnings from work as well as relatively high non-employment values, combined with a rather low degree of job-exit experiences. It may contain careers involving a longer gap in generally stable, but low-pay employment, yet also recent withdrawals from the low-wage labor market (early stage of the inactivity careers).

The cluster analysis confirms the theoretical assumption of the heterogeneous nature of employment precarity. The three core dimensions of precarious work careers come together in specific combinations, which are theoretically meaningful, thus validating the choice of these components. Each type of experience represents a distinct source of precarity and may or may not coexist with other forms of adversity. Low earnings and non-employment components, although highly positively correlated, in practice also occur in a contrasting combination. The low work intensity and job churning clusters in Germany and, to a lesser extent, the job discontinuity cluster in the USA are cases to the point. Aggregating the components in a composite index makes different labor market situations comparable with respect to the level of overall hardship.

4.3 Weighting the components of CNPI

The formula of the index gives the researcher a possibility to attach different weights to the components, thus prioritizing selected experiences. The default setting is to treat all components as equally contributing to overall precarity of the employment career. Applying differing weights may

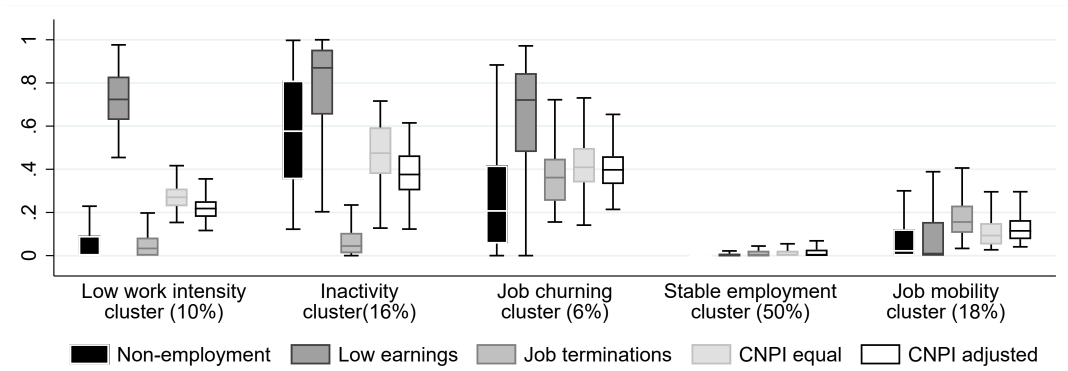
Table 1

Unconditional correlation coefficients between components of the CNPI and the composite index in Germany and USA

	Job terminations	Non-employment	Low earnings
Germany			
Non-employment	0.15	-	-
Low earnings	0.16	0.67	-
CNPI	0.36	0.86	0.92
USA			
Non-employment	0.11	-	-
Low earnings	0.07	0.76	-
CNPI	0.22	0.92	0.94

Data on 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence. Source: SOEP data for the years 2009–2017 (waves 2009–2018), and NLSY97 data for 2013–2018 (waves 2013–2019). Weighted sample; *N* = 3709 and 4630.

(a) *Germany*



(b) *USA*

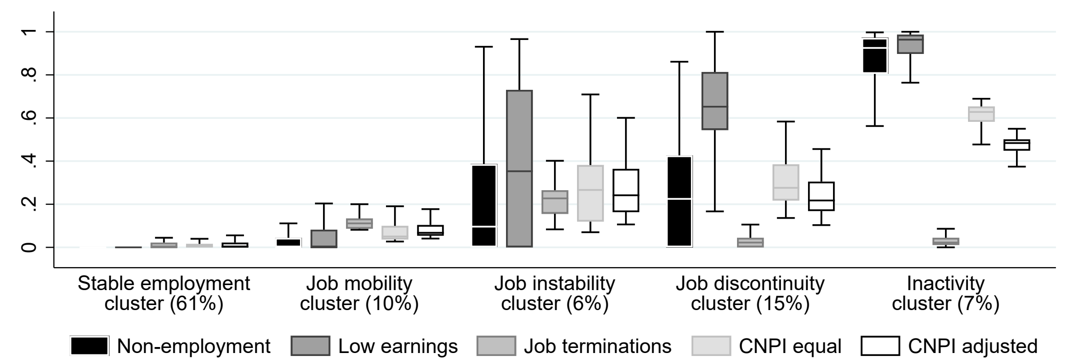


Figure 4

Longitudinal precarity profiles in Germany and USA. Data on 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence. Source: SOEP data for the years 2009–2017 (waves 2009–2018), and NLSY97 data for 2013–2017 (waves 2013–2019). Unweighted samples. In the USA the Black/Hispanic over-sample is excluded. N = 3709 *in Germany and 3505 in the U.S.*

be theoretically motivated or be a way to adjust for the underlying structure of the data. Data presented above show that in the CNPI there is substantial covariance between low earnings and non-employment components, which may warrant "downgrading" them in order to avoid "double counting" (Nardo et al., 2008) by giving more weight to the job terminations item. For illustration, we contrast the default setting (with equal weights for each of the components), with a specification attributing to the job termination component a weight two times higher than for the other two components (β=0.5, γ=δ=0.25). For the clusters discussed above we obtain different values of the index, depending on the specification (Figure 4). CNPI values increase against the default (equal-weight) specification for clusters characterized by higher levels of longitudinal experience of job instability, which slightly changes the order of clusters with respect to their average precarity. The two middle clusters in Germany swap their positions but the crude ranking remains stable. The overall correlation between index specifications exceets 0.98 in both countries.

Apart from the weighting parameters attached to each component of the index, there is a weight in the general formula for longitudinal adversity (Formula 2), which leverages the persistence of the experience against its recency-intensity – the α parameter. These two dimensions may have similar values, when hardship of high intensity tends to be experienced over subsequent years throughout a sequence. However, they can also diverge for sequences where either hardship of high intensity concentrates in the last years of a sequence, or low-intensity hardship is present over multiple years throughout the whole sequence. In this latter situation the α parameter changes the overall value of the component substantially, as illustrated by the low earnings component for Germany. Figure 5 presents the distributions of this component calculated with α=0.1 (maximum importance attributed to recency-intensity) and with α=0.9 (maximum importance given to persistence)[16]. We see how the values of the component shift to the right when higher importance is attached to persistence at the expense of recency-intensity. The concentration of the persistence-dominated component at the right end of the range pertains to individuals with stable earnings just below the low income threshold. This tendency may be better understood when confronted with the clustering solution from Figure 4, specifically, the low work intensity cluster, which is likely to produce high persistence and low recency-intensity values of the low earnings component.

In order to empirically assess the impact of weight setting on the index component values, it is instructive to look at the correlations between values obtained from different specifications. Table 2 presents the correlation coefficients for each CNPI component calculated using extreme weights (α = 0.1 and α = 0.9) in Germany and in the USA. We see that the correlations are very high, so different weights do not introduce a significant change in the relationships between the precarity components in both surveys.

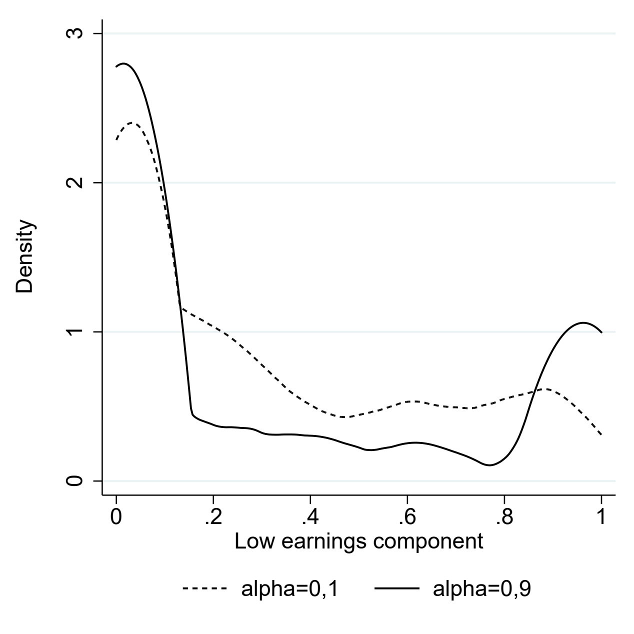


Figure 5

Distributions of CNPI low earnings component values with alternative specifications, Germany. Data on 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence and CNPI values above zero. Source: SOEP data for the years 2009–2017 (waves 2009–2018). Weighted sample: N = 2939.

4.4 Validity of CNPI

In the last step we investigate the criterion validity of the index. For these analyses we use the specification with parameter α = 0.5 and corrected weights of 0.5 for job terminations and 0.25 for non-employment and low earnings components (results for the alternative specification can be found in the appendix, Figures B6–B7).

[16]Similar results for the remaining components in both countries are included in the appendix (Figures B4-B5). While theoretically such differences may apply to all the index components, we have found that the value of α has little effect on the distribution of the longitudinal adversity of the non-work experience. In the case of job terminations, increasing the weight of persistence brings the values of the component closer to zero, suggesting that in both countries job loss or job change are not events experienced systematically over the course of many years. It also appears that the low income component in the U.S. follows a similar pattern to that observed in Germany.

Table 2

Correlation coefficients between contrasting specifications of 5-year CNPI components in Germany and USA

Component	Correlation between $\alpha = 0.1$ and $\alpha = 0.9$	
	Germany	USA
Job terminations	0.82	0.80
Non-employment	0.94	0.95
Low earnings	0.86	0.88

Data on 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence and CNPI values above zero. Source: SOEP data for the years 2009–2017 (waves 2009–2018), and NLSY97 data for 2013–2017 (waves 2013–2019). N = 2939 in Germany and 3434 in the U.S.

To examine the relationship between the components of the precarity index and subsequent labor market situation, we compare the distributions of the CNPI by employment status and type of contract for Germany (Figure 6a) and access to selected employee benefits for the U.S. (Figure 6b). In Germany, individuals employed on a permanent contract basis receive considerably lower values on the precarity index. For these respondents, the distribution of CNPI is heavily concentrated around zero. Individuals who do not report any work activity concentrate at higher levels of the precarity measure. The density plot of precarity among workers in fixed-term employment is flat, which suggests that fixed-term employment may as well accompany otherwise unproblematic employment careers.

In the U.S., we see a high concentration of low index values for individuals having access to all three employee benefit types in 2018. In contrast, sequences with higher CNPI scores tend to be followed by years during which individuals are not covered by any benefits. Nonetheless, the results point to an almost equal distribution of CNPI scores among respondents without any benefit coverage in 2018. This is a specificity of the U.S. labor market in which a significant segment of the working population, including people with relatively stable jobs and moderate earnings, still does not have access to basic benefits such as health insurance, retirement, or paid leave. This may suggest that “bad jobs” are not the same as precarious careers in the U.S. context.

This evidence is consistent with the results of multinomial logistic regression models (Figure 7; full regression results are provided in the appendix, Tables A9 and A10). Controlling for the level of education, marital status, age and gender, as well as race for the USA, higher values of CNPI obtained for the preceding five years increase the probability of being in a less advantageous labor market situation. In Germany, higher CNPI values are associated with a greater risk of staying out of work or being in fixed-term employment and a much lower chance of holding a permanent contract. In the U.S., the association pattern is similar and consistent with the theoretical expectation. The level of longitudinal precarity is negatively associated with access to benefits in the year succeeding the sequence.

Alternatively, we consider the association between the labor market situation at the beginning of a 5-year sequence and the CNPI value for this sequence. Again, we compare CNPI distributions (Figure 8) and present regression analysis results (Figure 9) for both countries.

We can conclude from descriptive evidence for Germany that sequences which start in permanent employment generate the lowest values of CNPI, whereas sequences starting in non-employment are related to high precarity levels. The “penalty” to the fixed-term contract, while visible, is not very large, which is also consistent with findings pointing to the mixed career effects of fixed-term employment on the German labor market (Gebel, 2010). We obtain a very similar picture for the USA. Sequences starting with individuals having access to all three types of benefits bulk heavily at very low values of the index. For sequences with no benefits in the beginning year the distribution of the CNPI values is fairly even. Lacking benefits may reflect higher exposure to labor market hardship, but may also be a feature of relatively stable jobs with wages above the low pay threshold, which do not evolve into precarious employment sequences.

The CNPI values predicted by the regression model are highest for respondents starting in a disadvantaged labor market position (Figure 9). Non-employment in the first year of the five-year sequence produces an estimated average degree of precarity of above 0.25, which is significantly higher than for sequences starting with fixed-term employment. The lowest average index values are estimated for sequences with a permanent contract at the beginning. In the US, we notice a huge difference in the estimated averages between sequences starting with work arrangements granting access to at least one benefit and those where there is no benefit coverage, either due to non-employment or employment with no such

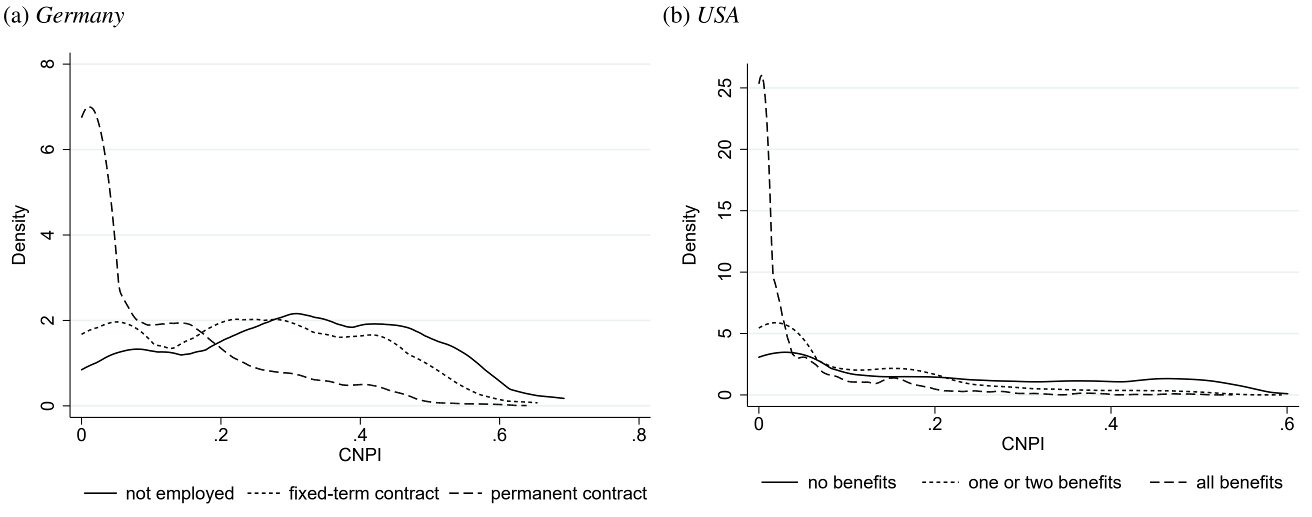


Figure 6

Distributions of adjusted CNPI[a] values of 5-year sequences by employment status (Germany) and access to employee benefits (USA) in the year 6. Kernel density plots. CNPI for 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence. Source: SOEP data for the years 2009–2018 (waves 2009–2018), and NLSY97 data for 2013–2018 (waves 2013–2019). Weighted samples: N = 2230 in Germany and 4546 in the U.S. The CNPIs are calculated using $\alpha = \beta = 0.5$ and $\gamma = \sigma = 0.25$. The benefits in the U.S. include health insurance, retirement plan, and paid leave. Individuals out of work are coded as having no benefits. Year 6 refers to the year following the sequence, i.e. 2014–2018 in Germany and 2018 in the U.S.

provision. Interestingly, the number of benefits granted has a weaker effect on the estimated CNPI value.

In a final step we investigate the mean values of the index across the age spectrum. Figure 10 presents the estimated average CNPI levels for individuals aged 25 to 67 (Germany) and 25–37 (the U.S.) in the last year of a 5-year sequence. In accordance with expectations derived from the literature, in Germany we find a u-shaped pattern of precarity levels across the life course. Higher CNPI values concentrate in early and late years of work lives, whereas prime aged workers experience on average a low level of labor market hardship. The U.S. data follow a similar pattern with respect to young and prime aged workers; data for older workers is unavailable in NLSY97.

4.5 Methodological issues

The analysis has shown that in empirical applications of the CNPI researchers must be very cautious about comparing absolute levels of the index (and each of its components) across countries when using national panel surveys - especially surveys that differ radically in the methodology of data collection, as in our illustration. While the theory-driven concepts used in the index refer to similar phenomena in different countries, interpreting the observed cross-country differences requires separating the "noise" caused by differing survey measurement approaches from the substantively meaningful effects of institutional contexts.

For instance, we find higher precarity levels in Germany than in the United States. Closer examination reveals that the difference between countries is driven by the job terminations and low earnings components, which are more clustered around zero in the U.S. With regard to low earnings it may be due to differences in the share of obligatory social insurance contributions in the gross earnings, which is substantial in case of Germany and much less relevant in the U.S. context. As a result, gross earnings in non-standard work arrangements in Germany, which are fully or partially exempt from social insurance contributions, fall below the low-earnings threshold (determined primarily by the wages of regular full-time employees covered by mandatory social insurance) to a much higher extent, compared to the expected pay differences in the lower segment of the U.S. earnings distribution. Furthermore, methodological differences in the way the data captures low earnings incidence may also play a role. The G-SOEP measure is based on the total reported gross annual income, which may be biased downwards, for instance, if people overlook additional money earned from supplementary jobs, overtime and bonus payments, and the like. The NLSY97 records income received from all jobs reported by the respondents, and explicitly asks (in a separate set of questions) about overtime payments, tips, and commissions. In addition, the U.S. wage data used to calculate CNPI

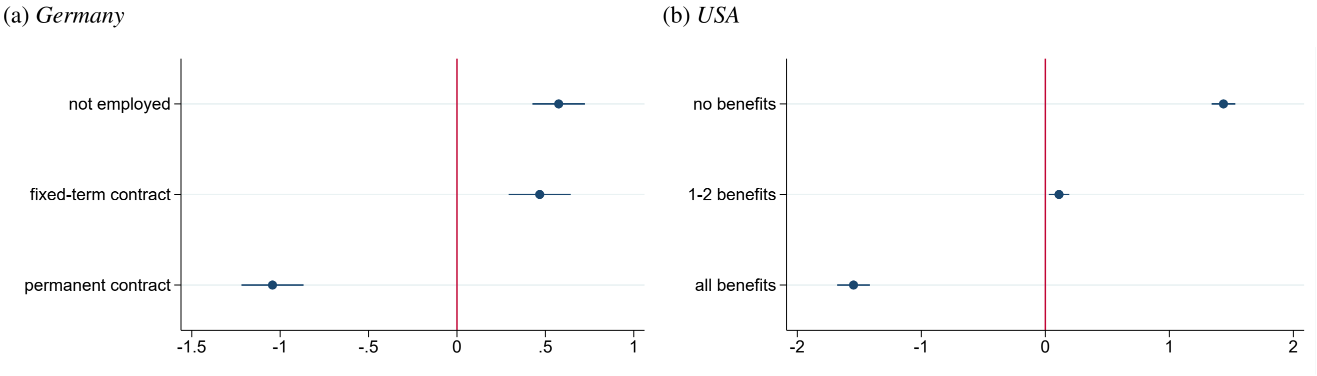


Figure 7

Average marginal effects of 5-year adjusted CNPI on employment status (Germany) and access to employee benefits (USA) in year 6. Multinomial logit with robust standard errors. Models control for education, marital status, age and gender (and race in USA). Source: SOEP data for the years 2009–2018 (waves 2009–2018), and NLSY97 data for 2013–2018 (waves 2013–2019). Weighted samples: N = 2230 in Germany and 4308 in the U.S. Full results are provided in table A9 and A10 in the appendix. See Figure 6 for specific remarks on the calculation of CNPI, the benefits used for the U.S. and the meaning of year 6.

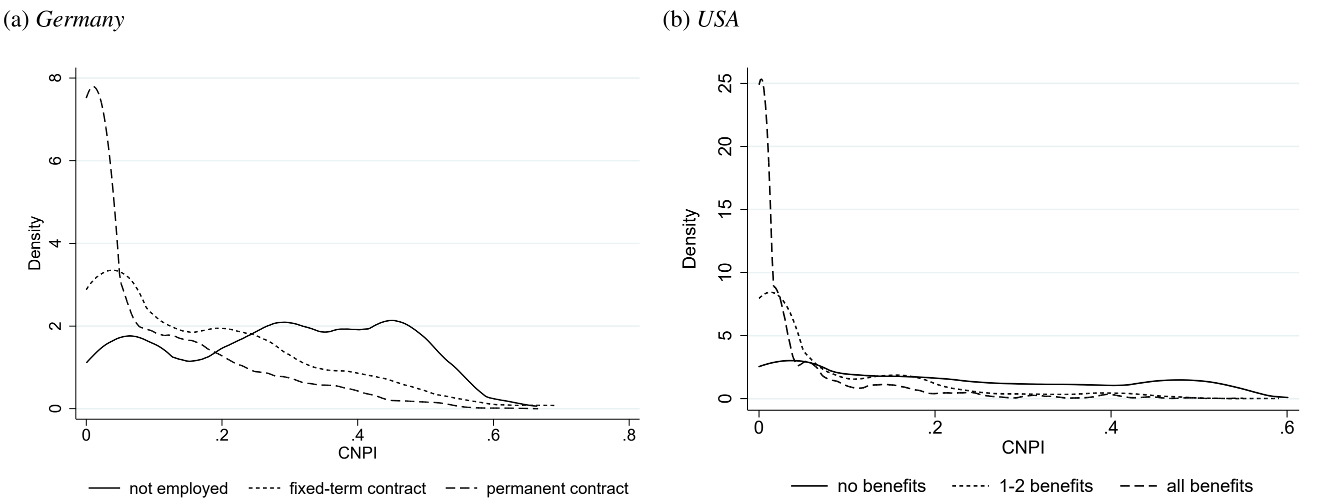


Figure 8

Distributions of adjusted CNPI values of 5-year sequences of individuals by employment status (Germany) and access to employee benefits (USA) in year 1. Kernel density plots. CNPI for 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence. Source: SOEP data for the years 2009–2017 (waves 2009–2018), and NLSY97 data for 2013–2017 (waves 2013–2019). Weighted samples: N = 3709 in Germany and 4628 in the U.S. Year 1 refers to the first year of the sequence, i.e. 2009–2013 in Germany and 2013 in the U.S. See Figure 6 for specific remarks on the calculation of CNPI and the benefits used for the U.S.

may be somewhat overestimated, as they concern the moment of the survey or the time the job ended in case of terminated jobs. Thus, they do not account for wage progression, which can lead to some degree of bias, especially in the case of long lasting jobs and individuals who did not participate in each wave of the survey in the period covered by the sequence. Biases can also arise with regard to jobs paid by the hour, if the actual weekly number of working hours changed throughout the duration of this job. Other methodological differences between the two surveys may also play a role, masking differences between countries. In particular, data allowing to estimate the number of job terminations was gathered differently, offering more detailed information for the U.S., but also forcing us to address the question how to treat

(a) *Germany* (b) *USA*

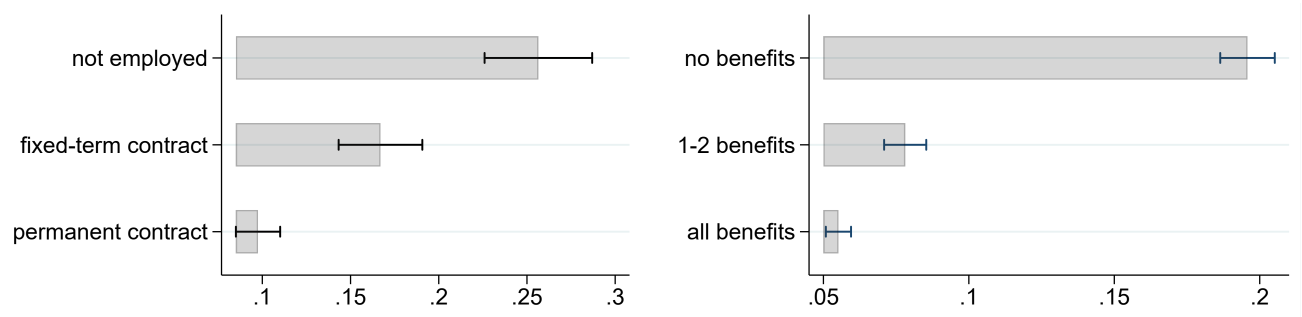


Figure 9

Predicted values of 5-year adjusted CNPI by employment status (Germany) and access to employee benefits (USA) in year 1. OLS regression with robust standard errors, dependent variable: CNPI adjusted. Models control for education, marital status, age and gender (and race in USA). Source: SOEP data for the years 2009–2017 (waves 2009–2018), and NLSY97 data for 2013–2017 (waves 2013–2019). Weighted samples: N = 3483 in Germany and 4570 in the U.S. Full results are provided in Tables A11 and A12 in the appendix. See Figure 6 for specific remarks on the calculation of CNPI and the benefits used for the U.S. See Figure 8 for the meaning of year 1.

within-job gaps which the respondents themselves do not define as job terminations, but which are associated with being out of work without pay for various reasons, sometimes for prolonged periods of time. With regard to joblessness, the G-SOEP data is based on self-reports of the respondent's activities in each month, while the NLSY97 does not use the calendar format for data collection, and work status during each month can be established only based on the beginning and end dates of all jobs and job gaps.

Various techniques may be used to at least partially address the possible bias caused by methodological differences between surveys used in cross-national comparisons. Drawing on recent developments in ex-post harmonization methods (Dubrow & Tomescu-Dubrow, 2016; Turek et al., 2021), control variables may be created to flag differences in survey design and account for their effects in regression models (Saris & Revilla, 2016; Slomczynski & Tomescu-Dubrow, 2018). Another possible method would be to estimate the size of potential bias by comparing different measures of adverse experiences. For example, the NLSY97 also collects information on annual income from work that is similar to the G-SOEP item. This information is collected once every two years and is available only for those who participate in a given wave (unlike the retrospective information on wages), so it cannot be used to compute the CNPI, but can be used to check the validity of cross-national comparisons. An additional possibility to assess the bias of the survey methodology would be to calculate the CNPI values using data from different national survey programs offering longitudinal career data and compare them within countries.

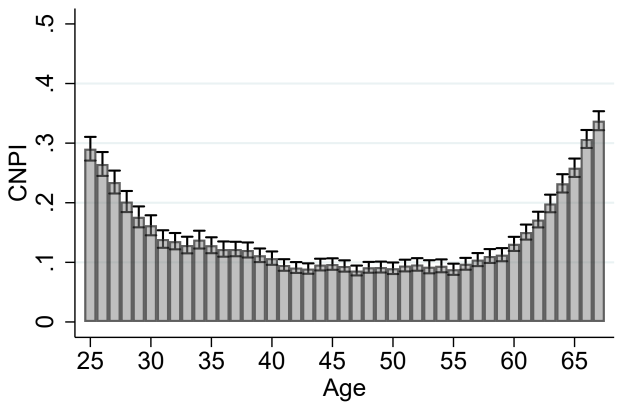
5 Discussion and conclusion

To address the challenges of cross-country analyses of EP, which arise from country-specific models of labor relations and legal environments, we propose a novel approach to operationalizing precarious work careers which makes use of national panel survey data. First, our conceptualization focuses on sequences of universal employment-related conditions and events, such as low earnings, periods of non-work and job terminations, which indicate weak labor market performance across different institutional contexts, thus facilitating cross-country analyses of precarious employment. Second, the proposed measure offers a dynamic perspective on labor market disadvantage by incorporating longitudinal information on individuals' employment histories. Building upon and extending recent work on cumulative deprivation indices, we develop sequence-based measures of the severity of adverse experiences which we combine to create a composite index of employment precarity, the CNPI.

The empirical application of the CNPI in two contrasting labor market regimes of Germany and the USA provides evidence for good construct validity of the measure in both institutional contexts. The data shows a high association between CNPI and country-specific indicators of job quality: type of contract (Germany) and access to basic employee benefits: health insurance, retirement plans, and right to paid leave (the U.S.). Initial descriptive analyses of the distribution of the index values in different subpopulations defined by the above characteristics are confirmed by results of inferential models, where the index served as an outcome variable or an explanatory variable.

Our results suggest that in cross-national comparative

(a) *Germany*



(b) *USA*

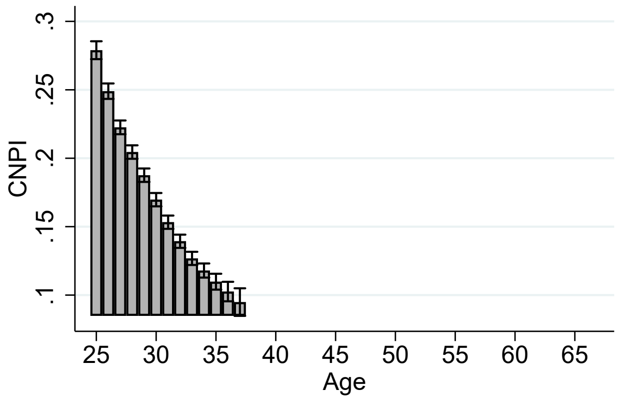


Figure 10

Estimated average 5-year CNPI values and 95% confidence intervals by age in Germany and the U.S. CNPI for 5-year sequences for individuals aged 25–67 (Germany) and 25–37 (USA) in the last year of the sequence, with at least one month in employment during the sequence. Source: SOEP waves 2003–2018 and NLSY97 waves 2003–2019 (covering the years 2003–2017). Weighted samples: $N = 71,756$ in Germany and 55,809 in the U.S. For Germany confidence intervals calculated on robust standard errors.

analyses of the effects of precarity, CNPI is able to capture more variation in labor market hardship, compared to measures focused on types of employment. This is especially the case in the U.S., where the most precarious non-standard or contingent employment arrangements are very rare, which is also typical for liberal labor market economies (e.g. Kalleberg, 2018). Even in Germany, where the type of labor contract does a better job of capturing differences in the exposure to EP, the CNPI offers a more nuanced picture of the heterogeneity within groups defined by type of contractual arrangement (Mertens & McGinnity, 2005; Reichelt, 2015; Westhoff, 2022). This is illustrated by the high variation of CNPI among fixed-term employees, suggesting that in some cases fixed-term contracts may accompany otherwise unproblematic employment sequences, and is consistent with the observation that many professional careers in Germany involve a prolonged period of consecutive fixed-term appointments reflecting the logic of professional advancement (Achatz et al., 2012).

Regarding the choice of the components of the CNPI, our theory-driven focus on non-employment, low earnings and job terminations is backed up by the results of cluster analyses showing that these dimensions present separate sources of precarity and come in different combinations which can be meaningfully interpreted in terms of country specific labor market and welfare regimes. The specifically German low work intensity cluster, which reflects the prevalence of marginal employment among female secondary earners in the conservative German welfare model, is one case to the point. A comparison between the job churning cluster in Germany and the job instability cluster in the U.S., which have the highest values of the job terminations component but differ in terms of overall precarity, offers a good illustration of the differences between the two labor market regimes—job loss appears to be less problematic in the context of a liberal economy.

Combining the three separate dimensions of precarious employment in an additive manner results in a comprehensive measure, which is able to capture different types of labor market weakness of individuals, and as such makes it possible to compare different employment careers with respect to their level of precarity. We argue that the usability of the CNPI to capture the overall level of labor market hardship of an individual at a given time point, taking into account their recent employment history, rests in the compound nature of the measure, allowing the representation of the multidimensional phenomenon of EP in a single metric. Additionally, each of the separate elements of the proposed composite index, and their dynamic properties of persistence and recency-intensity, has a meaningful theoretical interpretation as a measure of one (narrow) dimension of precarity. This allows for the observation of country-specific combinations of different aspects of labor market hardships, in order to better understand the drivers of precarity in each country.

Another potentially fruitful line of research involves using the CNPI to complement other analytical approaches to study employment careers and labor market hardship. In recent decades, methods of determining typical career patterns, using sequence analysis, optimal matching or hidden Markov models, have been intensively developed (Abbott, 1995; Pavlopoulos & Vermunt, 2015; Ritschard, 2021). While applications of these methods have provided many valuable outcomes in life course studies, including findings on employment careers, they also carry limitations. One of them stems from the fact that isolated events which may be relevant as signs of EP (e.g., a spell of joblessness at the end of an otherwise stable career) need not affect the classification of an individual sequence. Furthermore, sequence analysis approaches based on the alphabet of statuses typically do not account for transitions which do not result in an observable status change (e.g., employer changes during periods of continuous work). Hence, analyses complementing other approaches by the use of CNPI as an indicator can provide a richer picture of precarious careers in different societies (Struffolino, 2019).

A final remark concerns extending the CNPI framework to incorporate additional control variables reflecting the heterogeneity in the types of statuses other than work. In our specification, the CNPI only distinguishes work from non-work, in order to avoid making arbitrary judgments with regard to the potential "precariousness" associated with staying out of work for different reasons: education, parental leave, illness, unemployment (looking for a job but being unable to find one), or early retirement. Labor market inactivity may not be considered as a sign of adversity when it is entered into voluntarily, but it can also reflect withdrawal from the labor market by those who abandon searching for employment due to a limited availability of jobs. Different reasons for joblessness may have different interpretations, depending on the economic, cultural, institutional, and policy context - especially with regard to welfare benefits and unemployment policies. While the CNPI is conceptualized as independent of these country-specific differences, adding dummy indicators of various types of non-work activities to analyses using the index can provide a more nuanced picture of the varying life-circumstances behind high-joblessness sequences, allowing for substantive, theory-driven interpretations. This can be illustrated by the analyses of CNPI variation by age. The higher levels of EP among younger and older individuals, which reflect their weaker labor market position, can also be explained by schooling and retirement. Controlling for these statuses could allow researchers to separate these two effects. By including additional economic activity indicators to accompany CNPI, our proposal offers a comprehensive analytical framework for the study of precarity and the ways in which it can be moderated by different activities throughout the life-course in different countries. This carries a potential for a better understanding of both the country-specificity and the universal experience of labor market hardship.

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Appendix A
Tables

Table A1

Distribution statistics for total number of months in employment during a 5-year sequence, Germany and USA

Number of months in employment	Mean	SD	p25	p50	p75
Germany	51.58741	13.72387	47	60	60
USA	52.08364	14.89198	52	60	60

Notes: data on 5-year sequences for individuals aged 33-37 in the last year of the sequence. Source: G-SOEP data for the years 2009-2017 (waves 2009-2018), and NLSY97 data for 2013-2017 (waves 2013-2019). Weighted sample; N=3709 (Germany) and 4630 (USA)

Table A2

Distribution statistics for total number of job terminations during a 5-year sequence, Germany and USA.

Number of job terminations in a sequence	Mean	SD	p25	p50	p75
Germany	1.309860	1.390298	0	1	2
USA	0.872134	1.040958	0	1	1

Notes: data on 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence. Source: G-SOEP data for the years 2009–2017 (waves 2009–2018), and NLSY97 data for 2013–2017 (waves 2013–2019). Weighted sample; N = 3709 (Germany) and 4630 (USA)

Table A3

Distribution of years by number of job terminations (%), and average yearly number of job terminations, Germany and the U.S.

Yearly number of job terminations	Germany	USA
0	77.15	84.02
1	20.84	14.74
2	1.66	1.08
3 and more	0.35	0.16
Average	0.25	0.17

Notes: the yearly data concern the period 2009-2017 (Germany) and 2013-2017 (the U.S); for individuals who are included in the sample for the analysis of employment sequences (age 33-37 in the last year of the sequence, with at least one month in employment during the sequence). Source: G-SOEP waves 2009-2018, and NLSY97 waves 2013-2019. Weighted sample; N years=10861 (Germany) and 23150 (USA).

Table A4

Distribution statistics for the distance to low earnings threshold for years with the low earnings experience, Germany and the U.S.

N	Distance to low earnings threshold	Mean	SD	p25	p50	p75
Germany	5104	0.5893202	0.3442967	0.2627543	0.6520730	0.9410204
USA	2857	0.5747569	0.3566462	0.2338691	0.5621284	1

Notes: Data for years in which the total gross earned income was below 50% of the average gross earnings of full-time workers in the whole population. Data concern the period 2009-2017 (Germany) and 2013-2017 (the U.S) and respondents who are included in the sample for the analysis of employment sequences (age 33-37 in the last year of the sequence, with at least one month in employment during the sequence). Source: G-SOEP waves 2009-2018, and NLSY97 waves 2013-2019. Weighted samples: *N* years=5104 (Germany) and 8046 (USA).

Table A5

Descriptive statistics for variables included in the multinomial logit regression models of employment status, Germany

	Obs	Mean	SD	Min	Max
Dependent variable					
Employment status (ref. not working)					
Fixed-term contract	2230	.1332176	.339886	0	1
Permanent contract	2230	.7513751	.4323128	0	1
Self-employed	2230	0.00		0	0
Independent variables					
CNPI adjusted	2230	.1398117	.1558233	0	.6923443
Age	2230	35.03286	1.373608	33	37
Marital status, ref. married					
Married, living apart	2230	.0075304	.0864702	0	1
Single	2230	.4112357	.4921682	0	1
Divorced	2230	.0245061	.1546489	0	1
Widowed	2230	.0012348	.0351265	0	1
Education, ref. elementary and less					
Hauptschule	2230	.1517295	.3588389	0	1
Realschule	2230	.3209591	.4669498	0	1
Fachhochschulreife	2230	.0443863	.2059981	0	1
Abitur	2230	.1443132	.3514859	0	1
BA/ MA and above	2230	.331472	.4708479	0	1
Female	2230	.4870124	.4999434	0	1

Notes: Dependent variable: employment status in the year following the last year of the sequence (2014-2018). CNPI adjusted is measured for 5-year sequences for individuals aged 33-37 in the last year of the sequence, with at least one month in employment during the sequence. Calculated using component/dimension weights: $\alpha = \beta=0.5$ $\gamma = \delta=0.25$. Source: SOEP data for the years 2009-2018 (waves 2009-2018); weighted sample: N=2230.

Table A6

Descriptive statistics for variables included in the multinomial logit regression models of employee benefit coverage, USA

	Obs	Mean	SD	Min	Max
Dependent variable					
Benefits (ref. no benefits)					
1-2 benefits	4308	.1437027	.3508287	0	1
All benefits	4308	.4851723	.4998381	0	1
Independent variables					
CNPI adjusted	4308	.1064204	.146763	0	.6007324
Age	4308	35.00841	1.420014	33	37
Marital status (ref. single)					
Cohabitating	4308	.1255852	.3314198	0	1
Married	4308	.5475563	.497791	0	1
Legally Separated	4308	.0165175	.1274693	0	1
Divorced	4308	.0894601	.2854398	0	1
Widowed	4308	.0015255	.0390329	0	1
Education (ref. none)					
GED	4308	.0977575	.297021	0	1
High school diploma	4308	.3828159	.4861304	0	1
Associate/Junior college (AA)	4308	.0913149	.2880899	0	1
Bachelor's degree (BA BS)	4308	.2391867	.4266365	0	1
Master's degree (MA MS) PhD	4308	.1381223	.3450684	0	1
Female	4308	.4789469	.4996146	0	1
Race (ref. black)					
Hispanic	4308	.1318415	.3383577	0	1
Mixed Race (Non-Hispanic)	4308	.0106241	.1025363	0	1
Non-Black/Non-Hispanic	4308	.7211183	.4485013	0	1

Notes: Dependent variable: employee benefit coverage (health insurance retirement plan paid leave) in the year following the last year of the sequence (2018). CNPI adjusted is measured for 5-year sequences for individuals aged 33–37 in 2018, with at least one month in employment during the sequence. Calculated using component/dimension weights: $\alpha = \beta = 0.5$ $\gamma = \delta = 0.25$. Source: NLSY97 data for 2013–2018 (waves 2013–2019). Weighted samples: $N = 4308$.

Table A7

Descriptive statistics for variables included in the OLS regression models for adjusted CNPI, Germany

	Obs	Mean	SD	Min	Max
Dependent variable					
CNPI adjusted	3483	.1365039	.1530477	0	.6923443
Independent variables					
Employment status (ref. not working)					
Fixed-term contract	3483	.1468641	.3540212	0	1
Permanent contract	3483	.6475275	.4778087	0	1
Self-employed	3483	.0581334	.2340291	0	1
Age	3483	35.06135	1.393157	33	37
Marital status, ref. married					
Married, living apart	3483	.0119914	.1088622	0	1
Single	3483	.4260501	.4945722	0	1
Divorced	3483	.025614	.1580034	0	1
Widowed	3483	.0014575	.0381543	0	1
Education ref., elementary and less					
Hauptschule	3483	.1470195	.3541762	0	1
Realschule	3483	.3077121	.461613	0	1
Fachhochschulreife	3483	.0485758	.2150103	0	1
Abitur	3483	.1384223	.3453923	0	1
BA/ MA and above	3483	.3506341	.4772371	0	1
Female	3483	.4831867	.499789	0	1

Notes: Dependent variable: CNPI adjusted measured for 5-year sequences for individuals aged 33-37 in the last year of the sequence, with at least one month in employment during the sequence. Calculated using component / dimension weights: $\alpha = \beta$=0.5 $\gamma = \delta$=0.25. Employment status in the first year of the sequence. Source: SOEP data for the years 2009-2017 (waves 2009-2018) weighted sample: N=3483

Table A8

Descriptive statistics for variables included in the OLS regression models for adjusted CNPI, the U.S.

	Obs	Mean	SD	Min	Max
Dependent variable					
CNPI adjusted	4570	.1082084	.148044	0	.6322215
Independent variables					
Number of benefits (ref. none)					
1-2 benefits	4570	.1991063	.3993718	0	1
All benefits	4570	.4562311	.4981351	0	1
Age	4570	35.01203	1.418838	33	37
Marital status (ref. single)					
Cohabitating	4570	.1255742	.3314051	0	1
Married	4570	.5443338	.4980851	0	1
Legally Separated	4570	.0169406	.129063	0	1
Divorced	4570	.0903629	.2867323	0	1
Widowed	4570	.0014154	.0375993	0	1
Education (ref. none)					
GED	4570	.1020247	.3027138	0	1
High school diploma	4570	.3823312	.48601	0	1
Associate/Junior college (AA)	4570	.0913247	.2881018	0	1
Bachelors degree (BA. BS)	4570	.2354772	.4243431	0	1
Masters degree (MA, MS), PhD	4570	.1359997	.3428257	0	1
Female	4570	.4766494	.4995091	0	1
Race (ref. black)					
Hispanic	4570	.1316168	.3381106	0	1
Mixed Race (Non-Hispanic)	4570	.0108521	.1036179	0	1
Non-Black/ Non-Hispanic	4570	.7217433	.4481895	0	1

Notes: Dependent variable: CNPI adjusted, measured for 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence. Calculated using component /dimension weights: $\alpha = \beta = 0.5$, $\gamma = \delta = 0.25$. Employee benefits in the first year of the sequence include: health insurance, retirement plan, and paid leave. Individuals out of work are coded as having no benefits. Source: NLSY97 data for 2013-2018 (waves 2013–2019), weighted sample: $N = 4570$.

Table A9

Full estimation results, multinomial logit model for Germany (average marginal effects for CNPI reported in Figure 7a in the main article)

	Fixed-term contract (base category: permanent employment)		Not employed (base category: permanent employment)	
Independent variables	b	SE	b	SE
CNPI adjusted	6.343***	0.957	8.809***	0.996
Age	−0.029	0.078	−0.071	0.097
Marital status, ref. married	0.000		0.000	
Married, living apart	1.106**	0.373	−2.244*	0.881
Single	0.565*	0.263	−0.224	0.294
Divorced	−0.215	0.452	0.145	0.631
Widowed	2.901*	1.207	−44.575***	0.890
Education, ref. elementary and less	0.000		0.000	
Hauptschule	−0.844	0.601	1.780	1.315
Realschule	−0.898	0.527	1.248	1.257
Fachhochschulreife	−3.109***	0.806	0.290	1.315
Abitur	−0.689	0.630	0.717	1.261
BA/ MA and above	−0.549	0.539	2.054	1.261
Female	−0.418	0.312	0.153	0.309
Intercept	−1.013	2.866	−2.659	3.708

Multinomial logit model with robust standard errors, dependent variable: employment status in the year following the last year of the sequence (2014–2018). CNPI adjusted is measured for 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence. Calculated using component/dimension weights: $\alpha = \beta = 0.5$, $\gamma = \delta = 0.25$. Source: SOEP data for the years 2009–2018 (waves 2009–2018); weighted sample: $N = 2230$.

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table A10

Full estimation results, multinomial logit model for the USA (average marginal effects for CNPI reported in Figure 7b in the main article)

	1-2 benefits (base category: all benefits)		No benefits (base category: all benefits)	
Dependent variable	b	SE	b	SE
CNPI adjusted	5.088***	0.513	9.502***	0.442
Age	0.011	0.036	−0.042	0.031
Marital status (ref. single)				
Cohabitating	−0.165	0.173	0.070	0.150
Married	−0.326*	0.128	−0.117	0.111
Legally Separated	−0.306	0.474	0.397	0.350
Divorced	−0.461*	0.204	−0.076	0.169
Widowed	−0.457	1.218	−0.608	0.750
Education (ref. none)				
GED	−0.480	0.289	−0.359	0.254
High school diploma	−0.850***	0.256	−0.783***	0.226
Associate/Junior college (AA)	−0.989***	0.296	−0.890***	0.263
Bachelor's degree (BA, BS)	−1.439***	0.277	−0.990***	0.235
Master's degree (MA, MS), PhD	−1.768***	0.304	−1.398***	0.257
Female	0.067	0.108	−0.047	0.088
Race (ref. black)				
Hispanic	0.205	0.149	0.085	0.131
Mixed Race (Non-Hispanic)	0.349	0.565	0.797	0.437
Non-Black/ Non-Hispanic	0.136	0.128	0.317**	0.110
Intercept	−0.787	1.292	0.999	1.125

Multinomial logit model, dependent variable: employee benefit coverage (health insurance, retirement plan, paid leave) in the year following the last year of the sequence (2018). CNPI adjusted is measured for 5-year sequences for individuals aged 33–37 in 2018, with at least one month in employment during the sequence. Calculated using component/dimension weights: $\alpha = \beta = 0.5$, $\gamma = \delta = 0.25$. Source: NLSY97 data for 2013-2018 (waves 2013–2019). Weighted samples: $N = 43708$.

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table A11

Full estimation results, OLS regression model for Germany (expected values of adjusted CNPI by employment status reported in Figure 9a in the main article)

Independent variables	b	SE
Age	0.003	0.003
Marital status, ref. married	0.000	
Married, living apart	−0.004	0.033
Single	−0.014	0.012
Divorced	0.008	0.033
Widowed	0.034	0.018
Education, ref. elementary and less	0.000	
Hauptschule	−0.033	0.046
Realschule	−0.069	0.045
Fachhochschulreife	−0.128 **	0.047
Abitur	−0.064	0.047
BA/ MA and above	−0.094*	0.044
Female	0.092***	0.012
Employment form (ref. not employed)	0.000	
Fixed-term contract	−0.089***	0.017
Permanent contract	−0.159***	0.017
Self-employed	−0.068	0.044
Intercept	0.203	0.120
R-squared	0.307	

OLS regression with robust standard errors, dependent variable: CNPI adjusted, measured for 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence. Calculated using component / dimension weights: $\alpha = \beta = 0.5$, $\gamma = \delta = 0.25$. Employment status in the first year of the sequence. Source: SOEP data for the years 2009–2017 (waves 2009–2018), weighted sample: $N = 3483$

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table A12

Full estimation results, OLS regression model for the U.S. (expected values of adjusted CNPI by employment status reported in Figure 9b in the main article)

Dependent variable	b	SE
Age	-0.003^{*}	0.001
Marital status (ref. single)		
Cohabitating	-0.024^{***}	0.007
Married	-0.016^{**}	0.005
Legally Separated	0.010	0.017
Divorced	-0.029^{***}	0.008
Widowed	0.051	0.073
Education (ref. none)		
GED	-0.039^{**}	0.012
High school diploma	-0.069^{***}	0.011
Associate/Junior college (AA)	-0.077^{***}	0.013
Bachelors degree (BA, BS)	-0.112^{***}	0.011
Masters degree (MA, MS), PhD	-0.120^{***}	0.011
Female	0.069^{***}	0.004
Race (ref. black)		
Hispanic	-0.014^{*}	0.006
Mixed Race (Non-Hispanic)	−0.002	0.022
Non-Black/ Non-Hispanic	−0.009	0.005
Number of employee benefits (ref. none)		
1-2 benefits	-0.118^{***}	0.006
All benefits	-0.141^{***}	0.005
Intercept	0.375^{***}	0.051
R-squared	0.343	

Notes: OLS regression, dependent variable: CNPI adjusted, measured for 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence. Calculated using component/dimension weights: $\alpha = \beta = 0.5$, $\gamma = \delta = 0.25$. Employee benefits in the first year of the sequence include: health insurance, retirement plan, and paid leave. Individuals out of work are coded as having no benefits. Source: NLSY97 data for 2013–2018 (waves 2013–2019), weighted sample: $N = 4570$.

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Appendix B
Figures

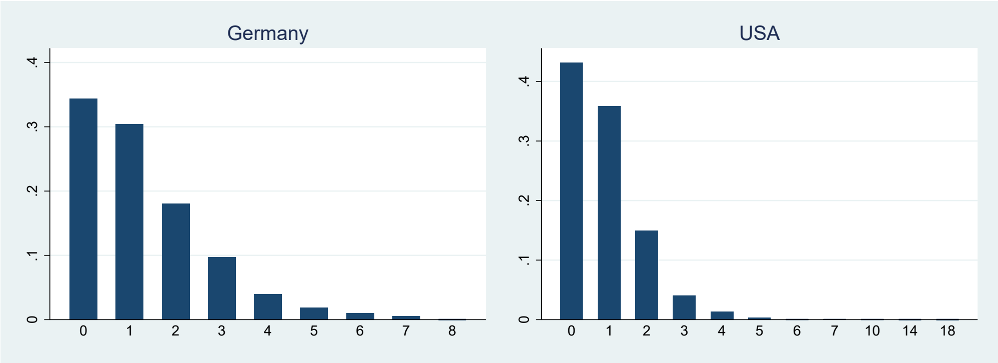

Figure B1

Distribution of the total number of job terminations in each sequence, Germany and USA. Shares of 5-year sequences with different total numbers of job terminations. Individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence. Source: SOEP data for the years 2009–2017 (waves 2009–2018), and NLSY97 data for 2013–2017 (waves 2013–2019). Weighted samples: N=3709 (Germany) and 4630 (USA).

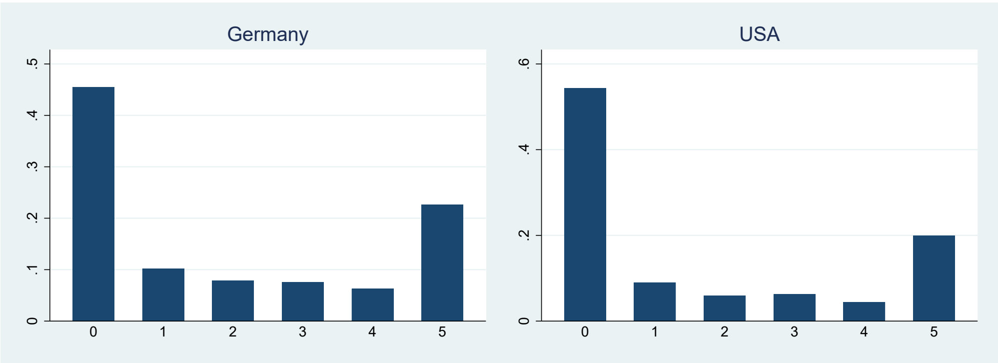

Figure B2

Distribution of the number of years with the low earnings experience in each sequence, Germany and the U.S. Data for 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence. Source: SOEP data for the years 2009–2017 (waves 2009–2018), and NLSY97 data for 2013–2017 (waves 2013–2019). Weighted samples: N=3709 (Germany) and 4630 (USA).

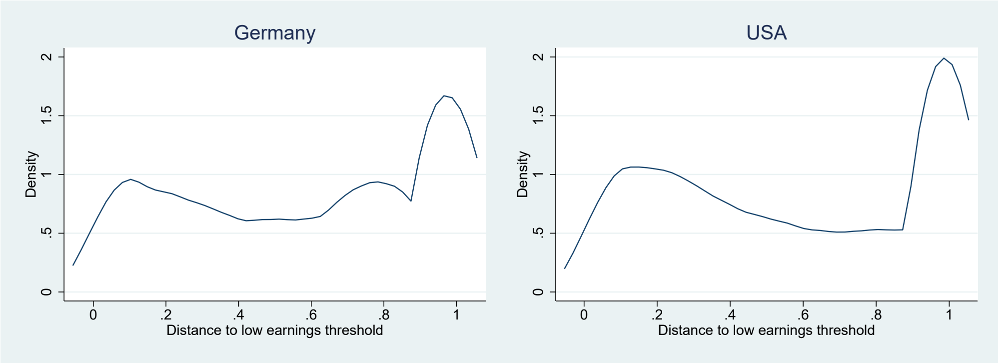

Figure B3

Distribution of the low earnings intensity in years with the low earnings experience, Germany and the U.S.Data for years in which the total gross earned income was below 50% of the average gross earnings of full-time workers in the whole population. Data concern the period 2009–2017 (Germany) and 2013–2017 (the U.S) and respondents who are included in the sample for the analysis of employment sequences (age 33–37 in the last year of the sequence, with at least one month in employment during the sequence). Source: G-SOEP waves 2009–2018, and NLSY97 waves 2013–2019. Weighted samples: N years=5104 (Germany) and 8046 (USA).

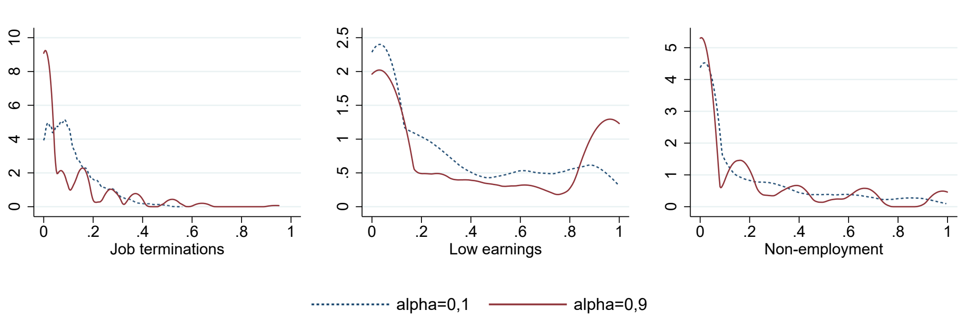

Figure B4

Distributions of CNPI components' values with alternative specifications with respect to weighting the component dimensions, Germany. Data on 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence and CNPI values above zero. Source: SOEP data for the years 2009–2017 (waves 2009–2018). Weighted sample: N=2939.

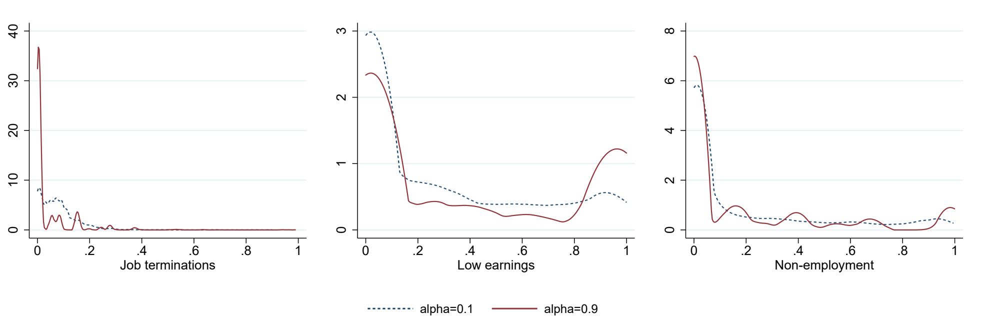

Figure B5

Distributions of CNPI components' values with alternative specifications with respect to weighting the component dimensions, USA. data on 5-year sequences for individuals aged 33–37 in the last year of the sequence, with at least one month in employment during the sequence and CNPI values above zero. Source: NLSY97 data for 2013–2017 (waves 2013–2019). Weighted sample: N=3434.

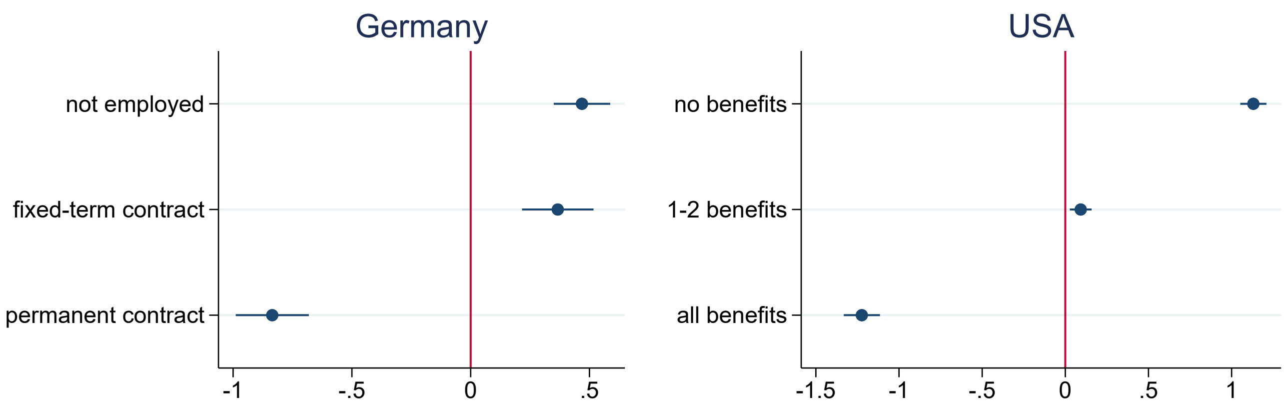

Figure B6

Average marginal effects of 5-year CNPI (calculated using equal weights for all components/dimensions) on employment status (Germany) and access to selected employee benefits (USA) in year 6. Multinomial logit with roubst standard errors. Models control for education, marital status, age and gender (and race in the U.S.). CNPI is measured for 5-year sequences for individuals aged 33-37 in the last year of the sequence, with at least one month in employment during the sequence. Benefits include: health insurance, retirement plan, and paid leave. Individuals out of work are coded as having no benefits. Year 6 is the year following the sequence: 2014-2018 (Germany) and 2018. Source: SOEP data for the years 2009–2018 (waves 2009–2018), and NLSY97 data for 2013–2018 (waves 2013–2019). Weighted samples: N = 2230 (Germany) and 4308 (the U.S.).

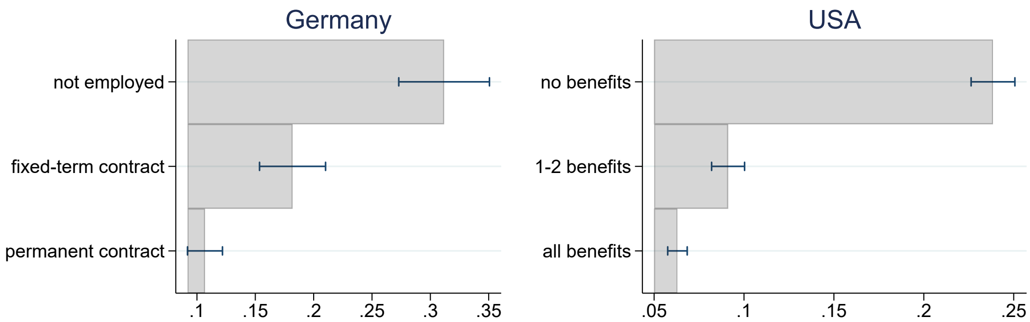

Figure B7

Predicted values of 5-year CNPI (calculated using equal weights for all components/dimensions) by employment status (Germany) and access to benefits (USA) in the year 1. Notes: OLS regression with robust standard errors. Models control for education, marital status, age and gender (and race in USA). See figure B6 for specific remarks on the calculation of CNPI and the benefits used for the U.S. Year 1 is the first year of the sequence: 2009-2013 (Germany) and 2013 (USA). Source: SOEP data for the years 2009–2018 (waves 2009–2018), and NLSY97 data for 2013–2018 (waves 2013–2019). Weighted samples: N = 3483 *(Germany) and 4570 (USA).*