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Career types and labor market structure: Intragenerational mobility in the United States

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A B S T R A C T

This article contributes to research on intragenerational mobility and careers by conceptualizing and measuring three types of orderly careers defined by patterns of attachment to and mobility among organizations and occupations: those that are focused on a particular employer; those centered in a single occupation; and those that span occupations. The latter is the most complex and we identify orderly careers that traverse occupations in two ways: (1) as sequential movement in occupational internal labor markets (OILMs), which are structures that enable upward job and wage mobility that we measure using data from the CPS and O*NET; and (2) as movement among occupational networks. We classify workers into career types from the bottom up, using their work histories in the NLSY. Our conceptualization of career types provides a link between labor market structures and intragenerational mobility by showing that orderly career types are associated with higher wages than disorderly careers and that OILM careers are related to greater wage growth.

1. Introduction

How people are allocated to positions in the system of social stratification is a long-standing topic in sociology. Much of the early research on this subject focused on intergenerational mobility (Blau and Duncan, 1967). More recent studies have emphasized intragenerational mobility, the persistent or secular upward or downward changes in individuals' job and economic positions over their working lives (Jarvis and Song, 2017). Research on mobility over the working life complements that on intergenerational mobility by specifying how labor markets and work structures influence the impact of persons' social and economic origins on their subsequent attainments. Studies of intragenerational careers have sought to understand how jobs are unequally rewarded and connected to each other, thereby providing routes to upward mobility, usually defined as increases in job rewards such as wages (e.g., Sørensen, 1974; Sacchi et al., 2016; Kalleberg and Mouw, 2018). A key question in this literature is how occupational structures and workers' individual characteristics and resources combine to shape careers and intragenerational job and economic mobility (Sørensen, 1974; Rosenfeld, 1992; Le Grand and Tåhlin, 2002; Shin, 2007; Manzoni et al., 2014).

Spilerman (1977) provides a foundation for incorporating occupational structures into the study of careers and intragenerational mobility. His sociological theory of labor markets posits that wages and other rewards are tied to jobs in firms and occupations (see also Kalleberg and Berg, 1987; Farkas and England, 1988). Therefore, understanding the movement of persons among these positions is essential for explanations of how socioeconomic achievement results from the interplay between labor market structures and individual characteristics. His analysis of cross-occupational mobility patterns identified "career lines" or pathways with a high probability of movement from one occupation to another. Some occupations are "portals" or the starting points of career lines, while others are not

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connected to other occupations. The notion of career lines was elaborated by Spenner et al. (1982), who showed that mobility rates between occupations vary greatly; some occupations are strongly connected by high rates of mobility while others are not (see also Sicherman and Galor, 1990's "career pathways").

Spilerman's sociological approach to intragenerational mobility and socioeconomic achievement diverges from the human capital theory's view of wages as tied to measures of an individual's human capital (e.g., education and experience—Mincer, 1974), as well as the status attainment perspective's emphasis on individual characteristics as primarily responsible for socioeconomic achievement (e.g., Blau and Duncan, 1967). Neither of these supply-side theories can explain how labor market structures combine with characteristics of individuals to generate inequalities in socioeconomic achievement.

Despite considerable progress in understanding how labor market structures shape patterns of job mobility and wage growth over a person's work history, several unresolved issues remain. One topic continues to be the identification of career lines, especially those that connect occupations. There are many possible moves across the detailed occupational structure, and occupational changes must be grouped into manageable patterns to explain cross-occupational career lines and the mechanisms that lead some occupations to be connected to others. Recent studies of occupational mobility networks use clustering algorithms to detect features of occupational structure based on the mobility rates between pairs of occupations (Cheng and Park, 2020; Lin and Hung, 2022; Toubøl and Larsen, 2017; Villarreal, 2020). The network-based approach is useful for identifying aggregate flows of workers between occupations but abstracts away from the mobility process of individual workers. Sequence analysis resembles Spilerman's career-lines approach as well as network models in that it attempts to find common patterns of occupational mobility using longitudinal data over a person's work history (Abbott, 1995; Aisenbrey and Fasang, 2017). Occupational sequences are generally highly aggregated, however, due to the complexity of possible occupational changes in a detailed occupational classification system (Fasang and Aisenbrey, 2022).

A second unsettled topic is explaining how job mobility is related to rewards such as wages and wage mobility. A common approach is to estimate growth curve models, which permit studies of inequalities in earnings and other job rewards over a complete work history (e.g., Fuller, 2008). Yet, growth curve models smooth over the continuities and discontinuities within careers because they have difficulty incorporating job and occupational changes other than through count measures (Bernhardt et al., 2001). Consequently, growth curve models better operationalize human capital and other supply-side theories rather than assess how labor market structures affect socioeconomic outcomes.

We address these two key issues in research on intragenerational mobility and careers: identifying patterns of job mobility; and linking career types to wages and wage dispersion. We build on Spilerman's notion of career lines to conceptualize orderly careers that span occupations. Studies of careers have primarily focused on attachment to a particular employer or a single occupation (Kalleberg and Mouw, 2018). Similarly, career instability is typically measured by studying employer and occupation changes. We identify a third career type, cross-occupational mobility, which is of two forms: (1) sequential movement in occupational internal labor markets (OILMs), which are structures wherein skill development, job ladders, and closure mechanisms create cross-firm mobility clusters linking several occupations (Althauser and Kalleberg, 1981); and (2) non-sequential movement among related occupational networks. We incorporate job changes and occupational mobility into our analysis of workers' careers and intragenerational mobility using workers' whole work histories in the 1979 National Longitudinal Study of Youth (NLSY).

We classify workers into one of four orderly career types (firm, occupation, OILM, network) or into a disorderly career type. We find that most workers in the 1979 NLSY cohort experienced one of the orderly career types. These form the structure of intragenerational mobility and are the building blocks for explanations of how labor markets shape job and economic mobility over the working life. We show that orderly career types are associated with higher wages than disorderly careers, reflecting the greater skills and experience that are accumulated within the different types of orderly careers. Our analysis of wage mobility in five-year periods across the life course demonstrates that workers do not experience an average continuous march of wage growth, but uneven wage growth from period-to-period over the work history. We then show that workers experience the largest wage gains when they change firms and remain in the same OILM.

2. Careers and career sequences

The *career* is a prominent concept in explanations of intragenerational mobility as well as in studies of work, organizations, life course analysis, vocational counseling, social psychology, management scholarship, among other fields. The ubiquity of the notion of careers reflects that it is "… an everyday word used by a variety of people, in a variety of contexts, from a variety of perspectives, for a variety of purposes, and with various levels of specificity or generality, focus or breadth" (Collin, 2009: 558). We define careers broadly as work histories held by persons over their working lives. While some persons may only have one job in their lifetime, most people change jobs, and we categorize their job mobility as representing different types of career sequences or career lines. Careers are made up of the career sequences (job spells) a person has over the working life course. Different combinations of career sequences produce different career types.

A central way of differentiating careers in academic research is by their *orderliness*, or the degree to which a sequence of jobs fits together as part of a logical or recognizable pattern, such as whether jobs are linked by characteristics such as occupational prestige or skills (e.g., Slocum, 1966; Gunz and Peiperl, 2009). Studies of careers by management and human resources scholars regard continuity over time as a central part of what defines a career. For example, Gunz and Mayrhofer (2011: 254) view a career as "a pattern in condition over time within a bounded social space," by which they mean that there is some boundary that links each successive state of the career to the previous state. Spilerman (1977) distinguished orderly career lines (whereby each subsequent job represented an increase in wages or status) from chaotic career lines, in which there is no progression in job rewards. Wilensky's (1961) pioneering article argued that orderliness is a key dimension of careers and a distinct feature of the social stratification system that is not reducible to education levels, unemployment spells, gender, race, occupational family (blue collar vs. white collar), or industry. He identified orderly vertical and horizontal occupational careers by cross classifying the direction of mobility (based on occupational prestige) and orderliness (based on similarity of skills). He found that no more than 30 percent of his sample of white, male persons in prime working ages in the middle mass of the Detroit area had orderly careers for half or more of their work histories. Nevertheless, having orderly careers had strong effects on social cohesion: men who spent at least 20 percent of their working lives in ordered careers had stronger attachments to the community, formal associations, and more robust contacts with kin, friends, and neighbors.

Spilerman, Wilensky, and stratification researchers have traditionally focused on occupations as structural sources of careers and inequality. The 500 or so occupations in the Census occupational classification system are meso-level units of analysis for studying labor market structures between jobs in firms and broad typologies of industry sectors or occupational families. Many studies of careers have focused on upward mobility within particular occupations (Goldin and Katz, 2016; Gorman and Kmec, 2009), typically on professions with defined boundaries. However, students of inequality have long recognized that organizations are also central to explanations of careers and inequality, a view that coincides with studies of careers and mobility within (and between) firms and other organizations (Baron et al., 1986; Kronberg, 2013). We need to integrate theories of occupations and organizations to identify types of careers and the opportunities available in the labor market (Arthur and Rousseau 1996; Handwerker and Spletzer, 2015; Wilmers and Aeppli, 2021).

Careers also differ in the *amount* of mobility or the number of changes in occupations and organizations. These job shifts also vary in their *direction*, whether they are upward or downward in terms of earnings, status, and non-economic job rewards. The amount and direction of mobility are the bases for two prominent and distinct conceptions of the structure of careers. A common perspective views careers as the *attachment* to an occupation or organization. Here, lengths of connection to occupations or organizations are used to categorize careers and people who change occupations or organizations are thus seen (at least implicitly) as changing careers (Farber, 2008). A second perspective sees careers as *patterns of movement* within and between occupations or organizations. Careers are viewed as resulting from mobility within a particular employer or shifts between employers that result in upward or downward movement, sometimes within an occupation, sometimes not. Some occupations are linked in career sequences that permit people to acquire skills that may be specific to these contexts (Kalleberg and Mouw, 2018).

The conception of careers as attachment to a single occupation or organization focuses attention on persons who remain with a single employer or an occupation for a substantial part of their working lives. These career types are relatively easy to measure. By contrast, the view of careers as patterns of movement between occupations emphasizes the *linkages* between occupations that enable persons to experience upward mobility. This type of career sequence is harder to operationalize given the large number of occupations and establishing such connections between occupations has presented a challenge for researchers studying careers and intragenerational mobility (Spilerman, 1977). Identifying and explaining occupational linkages that permit upward mobility is a primary task in this paper, though we also measure organizational and occupational careers.

3. Cross-occupational career lines

3.1. OILMs

A theoretical basis for explaining linkages between jobs is provided by the concept of internal labor markets, which occur within organizations (firm internal labor markets, or FILMs) or occupations (occupational internal labor markets, or OILMs). Both types of internal labor markets are characterized by a *sequence* of jobs that are: (a) linked by a job ladder; with (b) entry only at the bottom; and (c) movement up the ladder that is associated with the progressive development of knowledge or skill (Eyraud et al., 1990). The concepts of firm and occupational internal labor markets call attention to how individual worker characteristics and structural features of labor markets (represented by firms and/or occupations) shape workers' mobility over their careers.

OILMs resemble the orderly cross-occupational career lines in Spilerman's (1977) conception. OILMs are structural or institutional features of labor markets that account for why the incumbents of some occupations experience upward mobility without necessarily being tied to a particular firm. According to this view, some occupations can establish mechanisms of social closure (e.g., via union practices or licensing—see Weeden, 2002; Redbird, 2017) that restrict competition from non-occupational members and facilitate upward mobility within the occupation. The simplest case of an OILM is a highly closed, professional occupation (e.g., lawyer or physician) with direct transfer from education to work. Incumbents of these professional occupations may change firms as they progress in their careers. OILMs also enable the transfer of skills between "families" or clusters of occupations that permit incumbents to acquire greater skills through work experience that may be specific to these contexts. OILMs focus attention on how jobs within and across occupations are linked together to promote upward mobility. Organizational, occupational, and economic sociologists, as well as labor economists, tend to adopt this view and assess the impacts of movement within as opposed to between occupations as sources of upward trajectories in earnings (see Kalleberg and Mouw, 2018).

The mobility links between occupations suggested by OILMs resemble those identified by the recent literature in labor economics on task-specific human capital. By contrast to the standard human capital model's treatment of education and training as a single dimensional measure of skill-related productivity (Mincer, 1974), studies on task- and occupation-specific human capital show how the accumulation of specific skills increases the mobility rate along skill-based ladders between occupations (Gathmann and Schönberg, 2010; Gibbons and Waldman, 2004; Kambourov and Manovskii, 2009). Skills are often quite specialized and are useful only in occupations that have similar task and skill requirements. For instance, the skills that make someone a successful college professor will not directly translate into success as an auto mechanic.

Both the task-specific human capital and OILM approaches take occupations not as fixed or static, but as dynamically linked whether through skills or institutions. Studies by labor economists build on the notion of task-specific human capital to model careers as a process of skill formation whereby workers accumulate task-specific human capital that is transferrable across occupations (Gathmann and Schönberg, 2010; Gebicka, 2010; Holmes and Tholen, 2013; Pavan, 2011; Toledo et al., 2014; Yamaguchi, 2010, 2012). In these studies, a measure of task-specific human capital accumulation is added to traditional measures of overall work experience and firm experience in models predicting wages.

3.2. *Occupational networks*

An alternative approach to identifying cross-occupational career lines is by studying occupational mobility networks. Recent research uses clustering algorithms to detect the basic network of mobility channels connecting occupations based on the mobility rates between pairs of occupations (Cheng and Park, 2020; Lin and Hung, 2022; Toubøl and Larsen, 2017; Villarreal, 2020). A strength of the network approach is that it incorporates new statistical methods to operationalize career lines. The structure of the labor market can be conceived in network terms where jobs are nodes and the linkages between jobs, defined by the flows, are the edges (Tomaskovic-Devey, 2013). While Tomaskovic-Devey focuses on jobs defined in workplaces, his conceptualization is also applicable to jobs in particular occupations. A key stylized fact in his analysis of Swedish employer-employee registry data, for example, is that the labor market is “thin” instead of “thick” in the sense that few jobs are linked to each other, providing limited options for job seekers, and providing greater wage setting power to employers. The emerging literature in economics on “dynamic monopsony” that focuses on search frictions follows a similar theoretical logic (Ashenfelter et al., 2021).

Recent research on patterns of occupational mobility using network methods follows Spilerman (1977) by using a synthetic cohort approach to identify mobility pathways, typically using CPS panels. The network approach to studying careers is not able to characterize the sequential patterns of jobs that comprise individual work histories, however, nor can it incorporate individual-level characteristics into the analysis except as the average characteristics of (sending or receiving) occupations themselves (e.g., Lin and Hung, 2022). Nevertheless, network models are useful for identifying patterns of mobility between occupations that might be missed by the sequential OILM approach.

4. Measuring occupational linkages

The first step in identifying cross-occupation careers is to measure linkages among occupations that provide the mobility pathways for upward mobility. We adopt two approaches to measure the skill similarity between occupations: data on occupational mobility from matched samples of the Current Population Survey (CPS); and information on multiple dimensions of job skills from the O*NET. In each case, the strength of the linkage between occupations is the basis for our definition of a mobility pathway.[1] More details on our construction of these occupational similarity measures are found in Mouw et al. (2024).

4.1. *CPS mobility patterns*

Mobility patterns are the gold standard for identifying career lines. Some of this mobility reflects the transfer of skills from occupation A to occupation B. Other sources of this mobility might be mechanisms such as social networking, imperfect information, discrimination, unconscious bias, and so on.

We use data on occupational changes across successive months of the Current Population Survey (CPS) from 1994 to 2016 to measure the similarity between pairs of occupations, operationalized as the degree of mobility between them (cf. Spilerman, 1977; Spenner et al., 1982). We then construct a 0–1 measure of the relative mobility between occupations A and B as

$$\theta_{ab}^{CPS} = \frac{P_{ab}}{P_{ab} + P_{qb}},$$

where P_{ab} is the probability of mobility from occupation A to occupation B, and P_{qb} is the overall probability of moving to B from all other origin occupations Q excluding A. A value of 0.5 represents average mobility (i.e., where $P_{ab} = P_{qb}$), and numbers above 0.5 represent above average mobility between A and B. For any pair of occupations between which there is no observed mobility in the CPS data, we set θ_{ab}^{CPS} to 0.

4.2. *O*NET skill similarity*

An alternative measure of occupational linkages is the degree of skill similarity between two occupations. The assumption here is that a high level of mobility from occupation A to B (relative to the size of each) is likely if they have similar skill requirements. Our measure of occupational skill similarity uses the O*NET data, which provides information on 120 heterogeneous skill, ability, and

[1] By contrast, Wilensky’s (1961) approach coded occupations based on judgments regarding their prestige and other characteristics. A recent study by Osterman (2024) identified OILMs based on respondents’ perceptions of the extent of internal hiring within their organization, whether internal considerations play an important role in compensation, and whether the organization provides training; this operationalization does not distinguish FILMs from OILMs, however.

knowledge requirements (Hilton and Tippins, 2010). We use all 120 ratings, thereby preserving as much information as possible about the relationship between pairs of occupations. After assigning the O*NET skill ratings to the 3-digit Census occupation codes and standardizing each of the 120 ratings variables (to a mean of 0 and a standard deviation of 1), we calculate the "skill similarity" (θ_{ab}^{ONET}) as the correlation between pairs of occupations for the 120 ratings.

4.3. Comparing the O*NET and CPS occupational similarity measures

The O*NET and CPS similarity measures are positively correlated (0.45) in the 2000 Census occupational codes (for occupations with at least 100 cases in the CPS data). At the same time, it is informative to consider the differences between them (see Table 1). Although the CPS data do not provide a direct measure of skills, they may pick up institutional linkages and patterns of mobility between occupations that are missed in the expert evaluations in the O*NET data.

The CPS measure seems to do a better job than the O*NET at identifying occupations that are linked through mobility that might be thought of as a natural progression of task-specific skills and knowledge (i.e., order clerks → stock clerks and order filers), or perform more complex tasks that incorporate skills learned in the origin occupation (production workers→supervisors of production workers). In many cases the O*NET skill measures have difficulty explaining a high rate of mobility for workers from lower-level jobs to related managerial or supervisory occupations—or higher-level positions more generally—where success in the higher-level position is likely to depend upon a detailed knowledge and familiarity with the lower-level positions in ways that are not measured by the 120 O*NET variables.

5. Analyzing work histories

Attempts to study intragenerational mobility from a sociological perspective that incorporates job changes have foundered on the large number of possible moves among jobs. With 500 detailed occupations, for example, there are 124,750 pairs of occupations. In the observed data, shifts across occupations are highly clustered. However, a person may make multiple occupational moves over the life course. This quickly expands the number of possible occupational sequences, making it unwieldy to describe career lines in terms of

Table 1
A comparison of the CPS and O*NET similarity measures.

Panel A: High mobility in the CPS, Low O*NET similarity					
Origin occupation	**Code**	**Destination Occupation**	**Code**	θ_{ab}^{CPS}	θ_{ab}^{ONET}
Janitors and Building Cleaners	422	First-Line Supervisors of Janitors	420	0.920	0.141
Hairdressers, Hairstylists, Cosmetologists	451	First-Line Supervisors of Service workers	432	0.993	0
Taxi Drivers and Chauffeurs	914	Dispatchers	552	0.944	0
Stock Clerks and Order Filers	562	Wholesale and Retail Buyers, Except Farm	52	0.900	0
Painters, Construction and Maintenance	642	Construction Managers	22	0.867	0
Nursing, Psychiatric, and Home Health	360	Clinical Laboratory Technologists	330	0.862	0
Order Clerks	535	Stock Clerks and Order Filers	562	0.861	0
Maids and Housekeeping Cleaners	423	Hotel, Motel, and Resort Desk Clerk	530	0.849	0
Production workers, all other	896	First-Line Supervisors of Production workers	770	0.841	0
Food Preparation Workers	403	Chefs and Head Cooks	400	0.898	0.060
Panel B: Low mobility in the CPS, High O*NET similarity.					
Origin occupation	**Code**	**Destination Occupation**	**Code**	θ_{ab}^{CPS}	θ_{ab}^{ONET}
Dishwashers	414	Helpers, Construction Trades	660	0	0.828
Miscellaneous Assemblers and Fabric	775	Heavy Vehicle and Mobile Equipment	722	0	0.824
Sewing Machine Operators	832	Painting Workers	881	0	0.798
Packaging & Filing Machine Operators	880	Bus and Truck Mechanics and Diesel	721	0	0.768
Food Servers, Nonrestaurant	412	Butchers & Other Meat, Poultry, Fish	781	0	0.754
Cleaners of Vehicles and Equipment	961	Laundry and Dry-Cleaning Workers	830	0	0.740
Dishwashers	414	Pipelayers, Plumbers, Pipefitters,	644	0	0.730
Industrial Truck & Tractor Operators	960	Brick, Block, and Stone Masons	622	0	0.729
Interviewers	531	Heavy Vehicle and Mobile Equipment	722	0	0.726
Personal Care and Service Workers	465	Dispatchers	552	0	0.721
Bill and Account Collectors	510	Human Resources, Training, and Labor	62	0	0.720
Miscellaneous Agricultural Workers	605	Claims Adjusters, Appraisers, Examiners	54	0	0.719
Sewing Machine Operators	832	Highway Maintenance Workers	673	0	0.718
Dishwashers	414	Couriers and Messengers	551	0	0.716
Service Station Attendants	936	Industrial Truck &Tractor Operators	960	0	0.709
Bill and Account Collectors	510	Highway Maintenance Workers	673	0	0.708
Janitors and Building Cleaners	422	Bus and Truck Mechanics and Diesel	721	0	0.708
Maids and Housekeeping Cleaners	423	Market and Survey Researchers	181	0	0.688
Secretaries and Administrative Assts.	570	Fire Fighters	374	0	0.555
Customer Service Representatives	524	Drywall Installers, Ceiling Tile Installers	633	0	0.539
		Bill and Account Collectors	510	0.389	0.798
		Counselors	200	0.200	0.588

Note: "code" refers to the 2000 Census 3-digit occupation code.

discrete patterns of occupational sequences. Some researchers have stepped back and instead used a much coarser set of occupational categories (Dex and Bukodi, 2013; Fasang and Aisenbrey, 2022).

Spilerman's own approach was to study pairs of detailed occupation moves using the 1970 Census, and then compile sequences of changes together using a synthetic cohort approach. The problem with the synthetic approach is that it is unclear whether the same workers are moving from occupations A to B and then from occupations B to C. Moreover, patterns of career line job sequences are usually produced inductively, as done by Spilerman (1977) and Spenner et al. (1982) and more systematically via latent class analysis, factor analysis, or similar data reduction techniques.

Sequence analysis is often used to analyze career histories (Abbott, 1995; Biemann et al., 2012; Aisenbrey and Fasang, 2017; Blair-Loy, 1999; Dlouhy and Biemann, 2015; Fuller and Stecy-Hildebrandt, 2015; Halpin and Chan, 1998; Hollister, 2009; Joseph et al., 2012; Kovalenko and Mortelmans, 2014; Fasang and Aisenbrey, 2022; Van Winkle and Fasang, 2017) and resembles the career-lines and network models, in that it attempts to find common patterns of occupational mobility using longitudinal data. It is promising because it can take complex sequence data such as the occupational mobility among thousands of individuals and simplify it into a typology consisting of a small number of distinct patterns. Fuller and Stecy-Hildebrandt (2015), for example, use sequence analysis to examine the mobility of low-wage temporary workers in Canada and show that there are patterns of mobility missed by studies that focus on single spells of temporary work. Career lines defined in this manner could be grouped using theoretical constructs or algorithms, like factor analysis, and then analyzed.

Sequence analysis has been criticized as being overly sensitive to the *a priori* determined distance matrix that defines the similarity among individual sequences (Wu, 2000; Hollister, 2009; Warren et al., 2015) and for lacking techniques to assess the statistical significance of the resulting typologies (Levine, 2000), although recent research attempts to address these issues (Studer, 2021; Liao et al., 2022). For our purposes, a major limitation of the sequence analysis approach is that the large numbers of possible occupations (i.e., in this paper we use about 500 3-digit Census occupation categories) make operationalizing cross-occupation careers such as those in OILMs difficult using a sequence analysis approach, so most researchers opt for a smaller number of occupational categories. In a recent review of sequence analysis of careers, for example, Dlouhy and Biemann (2015) report that most researchers use between 6 and 16 different employment categories, with a high of 36. A typical approach is to reduce the number of possible states to be organized into sequences by distinguishing a worker's general work conditions defined by employment/unemployment, work hours, and large occupational categories (e.g., Fasang and Aisenbrey, 2022). Overall, we argue that while sequence analysis is successful in identifying typologies of different career patterns from individual work histories, it fails to incorporate the details of occupational and wage mobility envisioned by Spilerman's original conceptualization of career lines.

Using sequence analysis to study careers defines career continuity relative to previous jobs in the work history. As a result, career continuity and discontinuity can be empirically defined by looking at each worker's job history and considering whether each successive job change is consistent with the workers' previous history.

By contrast, our approach first identifies ideal type careers and then categorizes individual workers' careers into the typology. Our strategy for studying career types uses information on workers' detailed work histories to classify them into the types of orderly careers we discussed above: employer; occupation; and cross-occupations. The identification of orderly careers is not straightforward, as the complexity of work histories requires us to make assumptions about how best to categorize them. We provide estimates of the incidence of the orderly career types based on alternative assumptions, and regard workers whose careers do not fit into these categories as having "semi-orderly" or "disorderly" careers.

5.1. *Work histories in the NLSY data*

Our analyses are based on longitudinal data from the 1979 National Longitudinal Survey of Youth (NLSY). The NLSY work history data allow us to measure the timing and duration of jobs and job sequences, since it provides weekly data on respondents' main job and employment status over their whole work history. The 1979 sample includes persons born between 1957-1964 and aged 14-22 when first interviewed in 1979. In our main analysis, we include all jobs held after age 21 with non-missing wage and occupation data. We provide information on our sample in Tables 15 and 17, when we use our derived career types to help explain wages and wage growth. In the meantime, we use examples of individuals' work histories to illustrate the data and how we identify different types of career sequences and career types.

Table 2 presents the work history of respondent ID 427, a white woman with 12 years of education whose first job after the age of 18 was working as a waitress, but whose primary career is in advertising and marketing. The table reports information on each job she held in successive interviews. While the job and employment variables in the NLSY work history data are in a weekly array, information on job characteristics such as wages, occupations, and employers are updated every interview. Interviews were conducted once per year between 1979 and 1994, and then biannually after that. With respect to job and employment related variables, what we refer to as the "interview period" indicates the window of time from the previous interview to the current one. We organize the work history data to consist of sequential spells of employment with a particular employer between interviews, so each observation in Table 2 records information about a job held during this period. The employer ID (column 8) uniquely identifies employers in the respondent's work history, "start week" (column 4) shows the first week that a job with a particular employer is observed during the interview period, and "end week" is the last week a job is listed prior to the next interview.[2]

[2] The week numbers refer to the cumulative week calendar in the NLSY work history data. Jobs that continue over multiple interviews will have multiple observations in the data, and the "week" variable will be the last week of each interview period.

Table 2
Example Work History Data # 1 ID 427, White female, 12 years of education. (See the table notes for a description of the variables).

1 O#	2 Year	3 Age	4 Start Week	5 End Week	6 Wage	7 Exp	8 Emp ID	9 Occupation	10 Occ Code	11 Seq. OILM	12 Occ Net	13 Occ. Sim.
1	1978	20	0	10	12.74	10	1	Waiters and waitresses	435	1	2	
2	1978	20	30	51	15.38	21	2	sales workers, other commodities	274	1	1	0.642
3	1979	21	54	62	13.76	8	3	Secretaries	313	2	1	0.476
4	1980	22	62	122	9.67	60	3	Financial managers	7	2	1	0.377
5	1983[a]	25	232	302	15.69	70	4	Advertising and related sales	256	3	2	0
6	1985	27	304	382	15.69	78	4	Advertising and related sales	256	3	2	
7	1987	29	382	496	3.72	114	4	Purchasing agents and buyers,	33	3	2	0.796
8	1988	30	496	558	25.21	62	4	Advertising and related sales	256	3	2	0.800
9	1991	33	558	718	14.80	160	4	Purchasing agents and buyers	33	3	2	0.796
10	1994	36	718	852	22.25	134	4	Advertising and related sales	256	3	2	0.800
11	1996	38	852	981	33.19	129	5	Advertising and related sales	256	3	2	
12	1997	39	981	1028	20.71	47	5	Advertising and related sales	256	3	2	
13	2001	43	1028	1246	22.31	218	6	Managers, marketing, advertising	13	3	1	0.955
14	2006	48	1248	1485	25.48	237	7	Advertising and related sales	256	3	2	0.961
15	2008	50	1491	1608	27.40	117	8	Advertising and related sales	256	3	2	
16	2010	52	1644	1715	13.00	71	9	Managers and administrators, nec	19	3	1	0.612
17	2015	57	1745	1963	17.69	218	10	Public relations specialists	197	3	1	0.737
18	2015	57	1963	1981	19.01	18	10	Public relations specialists	197	3	1	
19	2017	59	2026	2053	15.05	27	11	Managers and administrators, nec	19	3	1	0.777
20	2018	60	2082	2134	17.59	52	11	Managers and administrators, nec	19	3	1	

Notes: The number in brackets refers to the column in the table.
[1] "O#" is the observation number, which is a sequential count of jobs nested within interviews (see the text for more information on the structure of the work history data).
[2] "Year" refers to the calendar year of the end of the job spell during the interview period.
[3] The person's age.
[4] "Start Week" refers to the first week a job is listed in the work history data during an interview period.
[5] "End Week" is the last week that the job is listed for a particular interview period.
[6] "wage" is the inflation adjusted wage, in 2010 dollars.
[7] "exp" is the incremental work experience in the job with a specific employer during this spell of employment within the interview period—This can smaller than the difference between the start and end weeks if there are employment gaps during this period.
[8] "empid" is a unique employer ID.
[9] "occupation" refers to 3-digit Census occupations, and [10] "Occ code" is the 1980 Census Occupation code.
[11] "seq OILM" is the sequential OILM career number, see Table 3.
[12] "occ net" is the network career number, see Table 3.
[13] "Occ. Sim" is the CPS occupational similarity between jobs where there is a change employer and occupation.
[a] Note that this job begins in 1982.

Columns 9 and 10 in Table 2 provide the occupation name and the 1980 3-digit Census code.[3] In her first four observations in Table 2, for example, person 427 worked in four different occupations—as a waitress, a sales worker, a secretary, and a financial manager. After that point, her occupational work history seems to pass the "eyeball" test of being an ordered career, even though it spans multiple employers and occupations. In observations 5–10, which cover the period from 1982 to 1994, she works for employer 4 in two occupations–advertising sales (3-digit occ code 256) and as a purchasing agent (code 33).[4] Although these two occupations represent different broad 1-digit occupational categories—purchasing agents are listed as a management occupation by the Census and advertising sales is a sales occupation, the CPS occupational similarity measure (column 13)—based on the relative degree of occupational mobility between two occupations—indicates that they are very related occupations. In observation 7, for example, the occupational similarity measure of 0.796 indicates a high level of continuity from advertising sales to purchasing agents—which suggests that these are similar occupations despite having separate 3-digit codes and labels.[5]

In the next section, we discuss the four different types of career sequences that we identify in the data, and then we return to Table 2 to illustrate them.

[3] See https://usa.ipums.org/usa/volii/occ1980.shtml for a full list of the 1980 occupations and 3-digit codes.
[4] Note that the job in observation 5 runs from week 233 (which is in 1982) to week 302 (in 1983).
[5] The CPS measure of occupational similarity is directional and can vary for two occupations, A and B, depending on the different rates of movement from A to B compared to B to A. For example, in observation 10, the similarity measure is 0.800 for movement from purchasing agents to advertising sales—slightly different than the 0.796 reported in in observations 7 and 9 for the reverse movement. By contrast, the O*NET measures capture skill similarity between A and B, but not whether B builds on A. Moreover, the O*NET measure likely describes similarity in general as well as OILM-specific skills. Hence, we rely primarily on the CPS measure in our analyses.

6. Measuring career sequences

6.1. Employer career sequences

Table 3 presents four types of career sequences or job spells in a person's work history in terms of employer and occupational attachment or mobility. The first type of career sequence is based on a job spell with a particular employer. Respondent 427 in Table 2 works for 11 unique employers, and the longest work spell for a single employer is 618 weeks for employer 4 in observations 5–10. This is 33.3% of her overall labor market experience of 1851 weeks (which is the sum of column 7 in Table 2 for these observations).

A job spell with an employer may involve changes in occupations. In this case, worker 427 moves back and forth between occupation 256 (advertising sales) and 33 (purchasing agents) within the same employer in observation 7 (1987) and 9 (1991). It is possible that this is an occupational coding error in that it might be hard to classify the "true" occupation that ID 427 is in, leading to repeated classification in both. Alternatively, these could be real occupational changes, as suggested by the lower hourly wages in the years spent as a purchasing agent. In either case, because they occur within the same employer, we consider them as the continuation of the same employer career.

6.2. Occupation career sequences

A second type of career sequence is based upon occupational attachment (type B in Table 3). In Table 2, respondent ID 427 works in 9 different occupations, but the count itself is misleading as most of her work history is concentrated in a small number of occupations. Her longest occupational tenure is in advertising sales, where she works 874 weeks (which is 47.2% of her total work history). The number of distinct occupational career sequences is simply the number of different occupations observed in the individual's work history data, and the degree of concentration in the largest sequence is the proportion of the total work history spent in the occupation with the most experience. In the case of ID 427, the person changes employers from #4 to #5 (in observations 10 and 11) but stays in the same occupation, thus continuing the occupational career.

6.3. OILM career sequences

Employer and occupational career sequences may miss career continuity that occurs in situations where *both* employers and occupations change. In fact, it is likely that the rate of reported occupational change increases when switching employers because either: (a) the internal job classifications are slightly different across employers; or (b) because the change in employers is associated with an upward move along a sequence of related occupations, even when it is clear to the worker (and the employer) that the new job is a continuation of the existing career. An example in the work history of ID 427 in Table 2 is the move from observation 12 to 13: the worker changes employers (from #5 to #6) and occupations (going from advertising sales [code 256] to "managers, marketing, advertising and public relations" [code 13]). The OILM approach argues that observations 12 and 13 are really part of the same career sequence: the CPS occupational similarity measure in column 13 for the movement from 256 to 13 is 0.955, indicating a very high level of similarity between these two occupations. This suggests that moving between these two occupations likely represents career continuity in advertising sales—just a movement into a management occupation in the same field. As a result, the career discontinuity between observations 12 and 13 may be spurious—i.e., an artifact of the way the employer and occupation approaches identify careers rather than a meaningful break in the worker's career sequence. A solution for the type of discontinuity observed between observations 12 and 13 in Table 2 is to link these jobs together into careers using our measures of occupational similarity derived from the CPS and O*NET.

The sequential OILM career sequence (C in Table 3) is based on the worker's history of occupations and employers, and it includes cross-employer sequences that are connected by similar (but not necessarily identical) occupations. We use the occupational similarity measure to compare the workers' occupations in year 1 to year 2, then year 2 to year 3, and onward. We define career continuity by observing the pattern of occupations and employers using sequences of three jobs based on the following rules. Table 4 lists three jobs (A, B, and C) that were held at three successive time points (T, T+1, and T+2). Jobs A and B are defined as in the same OILM career sequence if at least one of the following conditions is true.

1. A is linked to B in the same career sequence if they have an occupational similarity ("occsim") score of 0.6 or greater.
2. A movement into or out of management or supervisory "not elsewhere classified" positions in the same industry between A and B.[6] The CPS and O*NET similarity measures have a hard time dealing with "not elsewhere classified" ("NEC") occupations as they are combinations of multiple smaller occupations. Because transitions into management and supervisory jobs are frequently promotions on the same career ladder, we include them in our measure of OILM links.
3. A two-stage OILM where A and C are linked occupations (occsim>0.6), and B and C are with the same employer. The goal of this condition is to correct for the effect that occupation coding errors after changing employers have on career sequences, as we discuss below.

[6] These are occupations 19, 37, and 558 using the 1980 3-digit codes (see Footnote 3 for link to complete list of the 1980 occupations).

Table 3
Typology of career sequences.

Career Sequence	Description
A. Employer	A job spell with the same employer
B. Occupation	Cumulative experience in the same occupation. This type measures occupational labor markets (OLMs) or an occupational internal labor market (OILM)
C. Sequential OILM	Extends the sequence analysis approach, with a focus on individual career logic. Links employer spells that are connected by high levels of occupational similarity (Occsim > .6, see observations 12 and 13 in Table 2)
D. Occupational Network	Creates a network out of the individual's occupational history. In Fig. 1, the nodes of the network are yearly observations of an individual's occupations. The nodes are occupations in an individual's work history. The numbers on the nodes are the observation numbers in Table 5. All nodes in the network are connected, and the weights of the edges between nodes are the occupational similarity scores. We use a network clustering model to identify clusters of occupations within each individual's occupational network.

Table 4
Illustration of the OILM Sequential Career approach ("C" in Table 3)

Time	Job	Employer
(T-1)		
T	A	1
T+1	B	2
T+2	C	2
(T+3)		

Continuing with our discussion of respondent ID 427 in Table 2, we consider the identification of sequential OILMs based on these conditions. Column 11 shows the career number using this sequential OILM approach and the final column shows the occupational similarity measure between pairs of occupations. In going from observation 1 to 2, individual ID 427 changes employers, but stays in the same OILM because the occupational similarity between waiters and sales workers is 0.642. In going from observation 2 to 3, however, we start a new sequential OILM because none of the above conditions hold with respect to the mobility from jobs A to B in Table 4: she changes employers (going from 2 to 3) and occupations (going from sales work to secretaries). The occsim score of 0.476 in observation 3 is below the threshold of 0.6 and so there is no direct OILM link (condition 1), and neither occupation is a supervisory or managerial "not elsewhere classified" occupation (condition 2). Finally, although the two-stage OILM occupational similarity (linking jobs A and C in Table 4) isn't directly shown in Table 2 it also doesn't hold in this case (the CPS occupation similarity between the occupation in observation 4 [occ code 7] and observation 2 [occ code 274] is less than 0.6), so observation 3 starts a new career sequence for this worker.

In practice, we found that a substantial number of career sequences are connected by two-stage OILMs (condition 3) based on high occupational similarity between jobs A and C (from Table 4) that would otherwise be seen as discontinuous (based on OILM links between jobs A and B in condition 1)—and that in most of the cases were the same career sequence. Often a sequence of observations in the same or highly similar occupations is broken by an employer change to a dissimilar occupation only to subsequently resume the original sequence of similar occupations. Condition 3 thus incorporates flexibility in this sequential definition of a career to match an "eyeball" interpretation of what is going on in the data. Overall, the sequential OILM approach reduces the cumulative number of career changes observed in an individual's work history by connecting career-related sequences that involve simultaneous employer and occupational mobility.[7]

6.4. *Occupational network career sequences*

A shortcoming of the sequential OILM approach (C) is that it may miss patterns in the clustering of occupations within an individual's work history that aren't part of a temporally connected sequence of jobs. An alternative way to identify individual career sequences in the work history data is to use a network approach that ignores temporal ordering and identifies careers as clusters of similar occupations in the person's work history (D in Table 3). In the network approach, the nodes of the network are jobs—i.e., a specific occupation at a point in time—and the strength of the edges connecting the nodes are the occupational similarity scores (identical occupations have a similarity score of 1). In other words, all occupations are connected by the similarity measure even if they are not sequentially connected according to the three rules described in the previous section. The network approach looks backward on a person's job history and finds non-sequential patterns. By contrast, the sequential OILM apporach looks forward identifying whether

[7] We identify OILMs as a distinct type of career sequence in Table 3, but two other career sequences may also contain elements of OILMs. Some "occupation" career sequences, for example, may hide OILMs: more detailed occupational categories might reveal cross-occupation sequential movement within the Census occupation codes we use. Moreover, some "occupational network" career sequences may also represent OILMs, as when occupations held later in the work history build on the skills and other resources obtained in previous occupations but are linked more distantly than represented in Table 4.

the next job is linked to the one immediately preceding using the decision rules.

We use a modularity-based approach to detect communities in the network data (Liu et al., 2014; Newman, 2006) composed of the occupational histories. This approach has been used to identify the occupational structure at the macro level (e.g., Lin and Hung, 2022), and here we use it to identify occupational clusters within individual work histories. We use the random walk method for detecting network communities in the Igraph package in R ("cluster_walktrap"), which performed considerably better than the alternative methods given the small size of the individual occupational networks in the NLSY data.

Table 5 and Fig. 1 provide an example of the occupational network career sequence that provides a sharp contrast with a sequential OILM. In Table 5, we see that respondent 3737, a white woman with 12 years of education, has a long career with two employers. Her work history represents a single sequential OILM (column 11), because when she changes employers between observations 16 and 17, she stays in the same occupation. Nonetheless, despite the long employer and sequential OILM careers, there is a lot of occupational movement—she starts work as a machine operator, assembler, a clerk, and an inspector, then works as a biological and chemical technician, an editor, with several other occupations in between, and then works for 12 years as a production inspector from 2007 to 2019. The occupational network approach tries to look for patterns in these occupational data by creating a network based on the similarity of all the occupations in her work history, regardless of the timing of when they were held.

Fig. 1 graphs the clusters created by the occupational network approach.[8] The numbers on the graph correspond to the observation numbers in Table 5, and column 12 in Table 5 provides the network career number. The middle cluster in Fig. 1 (highlighted in green) is occupational network career #2. This connects a string of jobs at the start of ID 3737's work history (observations 1–7) to her work as a production inspector at the end of her career (observations 29–35) based on the clustering of occupational similarity scores among these occupations. In contrast, occupational network career sequence #1 is her work in the middle of her work history as an editor and a data entry keyer, and the third cluster is the work as a chemical and biological technician. The advantage of the occupational network career sequence type is that it can detect clusters of highly linked occupations that are not temporally adjacent.

6.5. *Overview of career sequences*

In this section, we provide descriptive information on the distribution of the four career sequences that form the bases of career types. We apply the decision rules in Table 3 to the NLSY work histories to identify the distinct career sequences. Table 6 shows the average number of employer, occupation, sequential OILM, and occupational network career sequences that workers had, along with the 25th, median, and 75th percentiles using each career sequence. On average individuals had 10.74 employers, 8.63 unique occupations and a considerably smaller number of career sequences based on the sequential OILM (3.31) and the network-based (2.81) approaches.

Table 7 shows the proportion of the individual's work experience spent in the longest career sequence.[9] These measures show much more similarity across the different career sequence types than the average counts in Table 6. Individuals spent about 53.2% of their time in their longest employer career sequence, and about 75.8% in their longest sequential OILM career sequence. Fig. 3 shows the corresponding distribution of these measures across all individuals in the data.

Table 8 shows the average count of career sequences by age. Tables 9a and 9b present information on the average number of career sequence types and proportion of the work history spent in the longest career sequence type by gender, race/ethnicity, and education. These tables show few differences in levels of career continuity among the four career sequence types for the different groups.

7. Measuring career types

The components of work histories—career sequences—that we identified in the previous section are the building blocks we use to classify an individual's overall work history as belonging to one of four career types, whether employer, occupation, sequential OILM or network career. The career types are retrospective assessments of the orderliness of job mobility over a person's work history (up to the workers' attrition from the survey or 2019).

We use two different approaches to identify career types. The first approach (V1) distinguishes beween four orderly career types (employer, occupation, sequential OILM, and occupational network) and a disordered career type. V1 is a "best fit" approach that identifies which of the four career sequences is the longest in the individual's work history. The second approach (V2) uses absolute thresholds (instead of relative thresholds in V1) to categorize each career type. This results in an additional career type, "unclassified," for respondents whose work history does not meet any of the thresholds for the other career types.

In the first approach (V1—best fit), we classify the worker's overall career type based on the mean standardized proportion of time in the longest career sequence m_{ij}[10]

(Eq. 1) $m_{ij} = p_{ij} - \overline{p}_j$,

[8] Our analysis uses cross-sectional measures of occupational similarity or occupational network clusters. However, the strength of occupational linkages may change throughout the work history of the NLSY cohort due to exposure to macroeconomic fluctuations such as technological change, economic recessions, and immigration. Future research should explore period-specific occupational linkages.

[9] The mean for each career sequence type is $\overline{p}_j$, used in Equation (1) below.

[10] We also tested classifications based on an entropy-based measure of career concentration in the longest sequences. The overall results are very similar, and we opted for the mean standardized approach because it is simpler.

Table 5
Example Work History Data # 2 ID 3737, White female, 12 years of education. (See the notes for a description of the variables).

1	2	3	4	5	6	7	8	9	10	11	12	13
O#	Year	Age	Start Week	End Week	Wage	Exp	Emp id	Occupation	Occ #	Seq. OILM	Occ. Net.	Occ. Sim.
1	1980	18	106	111	8.98	5	1	Miscellaneous machine operator	777	1	2	
2	1981	19	111	165	11.69	54	1	Miscellaneous machine operator	777	1	2	
3	1981	19	165	183	13.49	18	1	Miscellaneous machine operator	777	1	2	
4	1982	20	193	214	13.49	21	1	Miscellaneous machine operator	777	1	2	
5	1983	21	214	266	14.92	52	1	Assemblers	785	1	2	0.863
6	1984	22	266	319	17.54	53	1	Stock and inventory clerks	365	1	2	0.687
7	1985	23	319	371	19.02	52	1	Inspectors, testers, and grade	689	1	2	0
8	1985	23	371	397	21.34	26	1	Biological technicians	223	1	3	0
9	1986	24	411	426	21.34	15	1	Biological technicians	223	1	3	
10	1987	25	426	487	22.28	61	1	Operations and systems research	65	1	2	0
11	1988	26	487	549	23.94	62	1	Science technicians, n.e.c.	225	1	2	0
12	1988	26	549	558	24.71	9	1	Inspectors, testers, and grade	689	1	2	0.844
13	1989	27	563	607	24.71	44	1	Inspectors, testers, and grade	689	1	2	
14	1990	28	607	656	25.21	49	1	Inspectors, testers, and grade	689	1	2	
15	1990	28	656	658	24.20	2	1	Chemical technicians	224	1	3	0
16	1990	28	660	672	24.20	12	1	Chemical technicians	224	1	3	
17	1991	29	690	706	22.66	16	2	Chemical technicians	224	1	3	
18	1992	30	706	757	22.82	51	2	Biological technicians	223	1	3	0.932
19	1993	31	757	807	23.16	50	2	Biological technicians	223	1	3	
20	1994	32	807	863	23.39	56	2	Data-entry keyers	385	1	1	0
21	1996	34	863	958	24.49	95	2	Data-entry keyers	385	1	1	
22	1998	36	958	1060	25.40	102	2	Chemical	48	1	2	0
23	2000	38	1060	1176	28.68	116	2	Editors and reporters	195	1	1	0
24	2002	40	1176	1285	33.36	109	2	Editors and reporters	195	1	1	
25	2003	41	1285	1332	30.25	47	2	Editors and reporters	195	1	1	
26	2003	41	1335	1352	30.25	17	2	Editors and reporters	195	1	1	
27	2004	42	1355	1378	30.25	23	2	Editors and reporters	195	1	1	
28	2006	44	1378	1471	28.84	93	2	Editors and reporters	195	1	1	
29	2007	45	1471	1520	29.19	49	2	Production inspectors, checker	796	1	2	0
30	2008	46	1529	1573	29.19	44	2	Production inspectors, checker	796	1	2	
31	2010	48	1573	1686	32.00	113	2	Production inspectors, checker	796	1	2	
32	2012	50	1686	1827	30.31	141	2	Production inspectors, checker	796	1	2	
33	2014	52	1827	1927	30.21	100	2	Production inspectors, checker	796	1	2	
34	2017	55	1927	2052	32.77	125	2	Production inspectors, checker	796	1	2	
35	2019	57	2082	2151	33.84	69	2	Production inspectors, checker	796	1	2	

where p_{ij} is the proportion of individual i's work history spent in the longest career sequence of type j, and $\bar{p}_j$ is the average of p_{ij} among all the individuals in the sample for a particular career type (listed above in Table 7).[11] The m_{ij} that is the largest among the four career sequences from Table 3 is used to classify the overall career type for that worker. The exception is that if $m_{ij} < 0$ for all four career types—i.e., if the individual has below average career concentrations for all four career sequences—then we classify the career as "disorderly". We note that the degree of order or disorder in a career depends upon the logic used to classify a particular career sequence (i.e., each of the approaches in Table 3)—so that the disorderly classification just indicates that the work history doesn't fit well into any of the four approaches, not that it is maximally "disordered" (i.e., with an extremely low m_{ij}) on any particular one of the four types of career sequences. Table 10 illustrates the overall career type classification for the two respondents we have discussed so far, 427 and 3737. For these two respondents, the cells show the proportion of the work history spent in the longest career sequence for each type, p_{ij}, and the mean standardized m_{ij} is in parentheses. We classified both workers as having sequential OILM career types (using the best fit classification) because they are both in long sequential OILM career spells resulting in a high value of m_{i,seq_OILM} (in column 11 of Table 5).

Table 11a lists the classification rules for V2 of the career type variable. We start by defining an employer career as one where the worker's longest employer sequence comprises at least 0.7 of their overall work history (in terms of weeks of experience).[12] We based this threshold on the distribution of the overall longest employer spells shown in Table 7 and Fig. 3. As shown in Table 7, 0.7 is close to the cutoff for the 75th percentile of the longest employer spell in this data. Next, we define an occupational career as one where the longest occupational sequence is greater than 0.6 of the work history. In addition, we require that the longest occupational spell is

[11] We mean standardize in Equation (1) to focus on the relative degree that each respondent's work history fits into a specific career type; average differences in $\bar{p}_j$ among the different career sequence types in Table 3 will depend upon the specific logic of each approach so m_{ij} is a better measure of relative fit.

[12] In discussing these classification rules, the numbers in this paragraph refer to the proportion of the weeks worked in a particular job spell divided by the total number of weeks of works in the respondent's work history.

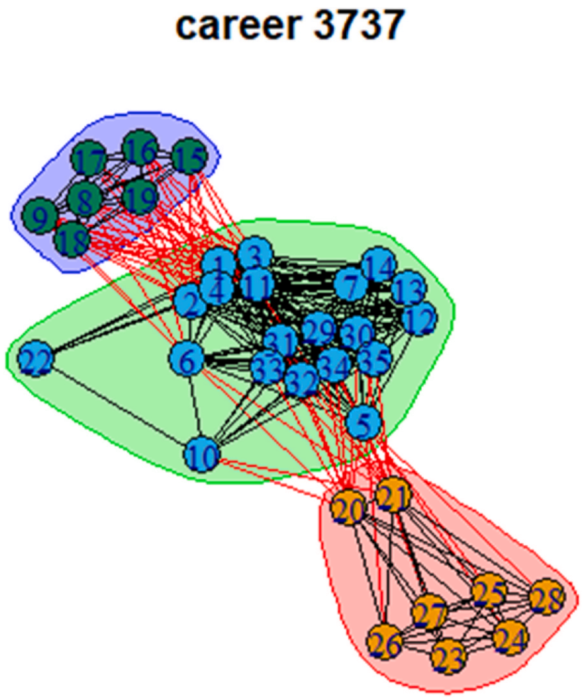

Fig. 1. Occupational Network for ID 3737.
Occupations in an individual's work history are nodes, the strength of the edge between nodes is the CPS occupational similarity measure. (The numbers in the nodes are the observation numbers from Table 5). The nodes are clustered using the "cluster walktrap" algorithm from the Igraph package in R.

Table 6
Average number of career sequence types.

Career Sequence Type	Mean	Percentile		
		p25	p50	p75
Employer	10.74	5	9	15
Occupation	8.63	6	8	11
Sequential OILM	3.31	2	3	4
Occupational network	2.81	2	2	3

greater than the longest employer spell. This ensures that occupational careers include multiple employer spells—i.e., they are not simply a long occupational spell within the same employer. We then define a sequential OILM career as one where the longest OILM is at least 0.95 of the overall work history (again referring to the 75th percentile to identify a reasonable threshold). In addition, we require that the longest sequential OILM spell is at least 0.2[13] longer than the longest employer spell; this ensures that we are connecting at least two employer spells together through an OILM connection, and not simply relabeling a long employer spell as an OILM spell. Similarly, an occupational network career is defined as the longest occupational network spell greater than 0.9 (of the work history) and longer than the longest employer spell by 0.2. We define disorderly careers as ones where there is no employer or occupational spell greater than 0.4 (of the work history), and no OILM or network spell greater than 0.7. Finally, the "unclassified" category subsumes all the cases that don't fit into any of the previous categories based on these decision rules; this represents a middle ground ("semi-ordered") between disorderly careers and the numerical thresholds used to define an "orderly" career for each of the four career types.

Table 11b shows the distribution of career types for these two classification approaches. For the best-fit approach in V1, 19.75 percent of workers in the NLSY79 have employer careers and another 21.78 percent have occupation careers, in contrast to 20.37 and 12.01 for the absolute-level approach in V2. Overall, 23.22 percent of workers in this cohort are categorized as having disorderly careers using the "best fit" approach, which classifies them as disorderly if they are below average in their career concentration m_{ij} for each approach. This compares with the 34 percent of workers that Wilensky (1961) found as having disorderly careers. By contrast,

[13] We use this (arbitrary) figure to adjust for the fact that the mean level is much higher for OILMs than employer spells (as it combines employer spells together).

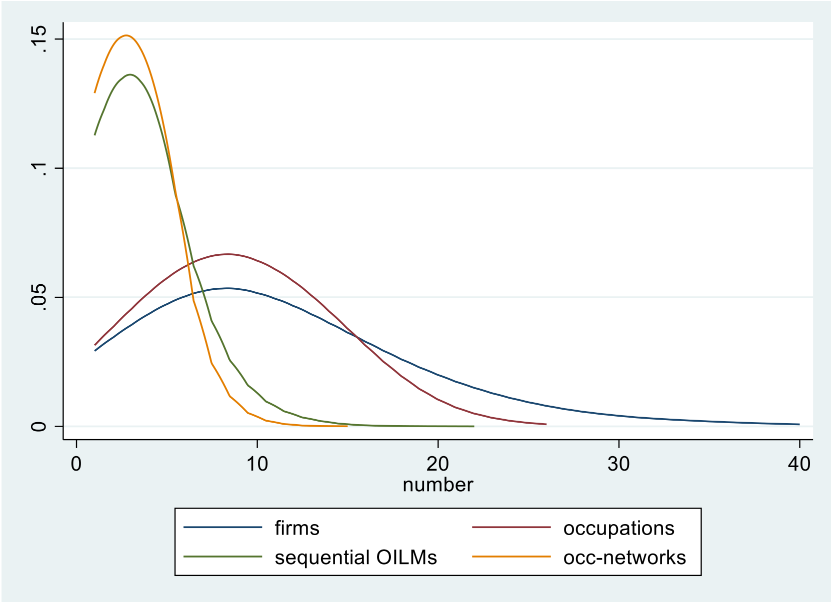

Fig. 2. Number of different firms, occupations, and careers in individuals' work histories.

Table 7
Proportion of an Individual's work history spent in longest career sequence, by career sequence type (see Table 3).

Career Sequence Type	Mean	p25	p50	p75
Employer (i.e., longest employer spell)	0.532	0.336	0.491	0.707
Occupation	0.510	0.345	0.471	0.644
Sequential OILM	0.758	0.571	0.801	0.983
Occupational network	0.710	0.561	0.697	0.862

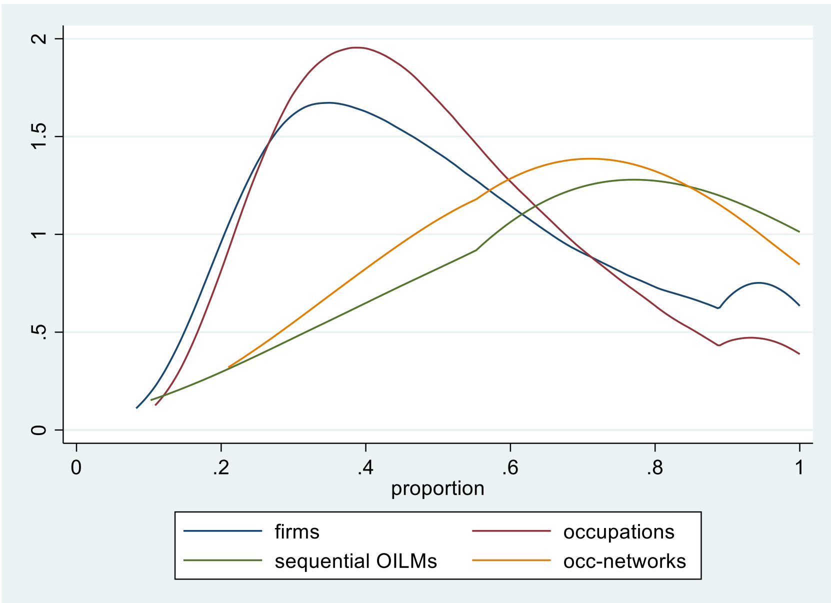

Fig. 3. Distribution of the proportion of an Individual's work history spent in longest career sequence, by career sequence type.

Table 8
Cumulative number of firms, occupations, sequential OILM and occupational network career sequences by age.

Age	Employers	Occupations	Sequential OILM	Occupational network
25	5.84	4.46	2.07	2.18
30	7.52	5.96	2.50	2.49
35	8.54	6.71	2.76	2.62
40	9.30	7.15	2.95	2.70
45	9.87	7.46	3.10	2.75
50	10.29	7.68	3.20	2.78
55	10.62	7.84	3.28	2.81

Table 9a
Average number of career sequences by demographic group and education.

Career Sequence Type	All	Men	Women	<=High School	College+	Hispanic	Black	White
Unique employers	10.74	11.15	10.32	10.25	11.38	11.33	11.30	10.34
Unique occupations	8.63	9.11	8.67	8.42	8.32	9.30	9.32	8.61
Sequential OILM	3.31	3.27	3.35	3.14	3.49	3.39	3.53	3.20
Occupational network	2.81	2.89	2.73	2.68	3.03	2.92	2.86	2.76

Table 9b
Proportion of an individual's work history spent in longest career sequence type, by demographic group and education.

Career Sequence Type	All	Men	Women	<=High School	College+	Hispanic	Black	White
Employers	0.532	0.530	0.535	0.538	0.532	0.518	0.520	0.541
Occupations	0.510	0.511	0.509	0.514	0.525	0.506	0.508	0.512
Sequential OILM	0.758	0.767	0.748	0.759	0.775	0.751	0.744	0.765
Occupational network	0.710	0.710	0.710	0.717	0.718	0.703	0.702	0.715

Table 10
Career type classification for ID 427 and 3737.

ID	Career type classification (version 1, "best-fit")	Proportion of work history spent in longest career segment (mean standardized proportion in parentheses)			
		Longest employer	Longest occupation	Longest Seq. OILM	Longest Occ. Net.
427	Sequential OILM	0.334 (−0.198)	0.472 (−0.037)	0.947 (0.188)	0.626 (−0.084)
3737	Sequential OILM	0.726 (0.193)	0.329 (−0.181)	1 (0.242)	0.627 (−0.083)

Table 11a
Classifications of career types, version 2 ("absolute level").

Career Type	Version 2: "Absolute level" career type
	(Numbers refer to the proportion of the individual's overall work history)
Employer	Longest employer spell >0.7 (of the individual's work history)
Occupation	Longest occupational spell >0.6, and longer than the longest employer spell
Sequential OILM	Longest sequential OILM spell >0.95 and exceeds the longest employer spell by 0.2
Occ Network	Longest occ. network spell >0.9 and exceeds the longest employer spell by 0.2.
Disordered	Longest employer and occupation spells <0.4, and the longest sequential and network spells are <0.7
Unclassified	None of the above conditions is true

13% of workers are classified as having disorderly careers using the stricter definition of disorderly from V2.

Table 11c provides a cross-classified table of the joint categorization of both versions of the career type variable to allow for clearer comparison, with the best-fit version (V1) on the rows and the absolute-level version (V2) in the columns. Looking across the rows, we see that 619 of the employer types in V1 are categorized in the "unclassified" group in V2, because they don't meet the 0.7 threshold for longest employer career. The V1 occupational career type is that most affected by the V2 classification scheme, with 721 cases being reclassified as employer careers (because of the requirement in V2 about the relative length of the longest occupation and employer career spells). In addition, in Row 5 of Table 11C we see that the V2 version of the disordered career type is largely the result of splitting the V1 category into two parts—disordered and unclassified careers.

In Table 12, we identify occupations that have a high prevalence of appearing in the longest career spell of workers who are categorized in each of the four orderly and the disorderly career types, using the best-fit version (V1) of career types. Postal clerks, firefighting occupations, and farmers are highly prevalent occupations in employer careers. So too are distribution supervisors,

Table 11b
Distribution of career types.

	Version 1: "Best fit" career type[1]	Version 2: "Absolute level" career type[2]
	Percent	Percent
Employer	19.75	20.37
Occupation	21.78	12.01
Sequential OILM	16.71	11.26
Occ network	18.53	13.87
Unclassified		29.39
Disordered	23.22	13.09
Total	100	100
N	12,686	12,686

Notes.
[1] Classification based on Equation (1) in the text.
[2] Based on the classification rules in Table 11A.

purchasing agents and buyers, industrial machinery repairers, and electrical power installers and repairers. The common thread of these occupations looks to be government employment or jobs in stable industries with large employers. For occupational careers, physicians and lawyers top the list of occupations, which is unsurprising given their high degree of occupational closure. Other occupations with closure through licensure and other mechanisms are dental hygienists, hairdressers and cosmetologists, registered nurses, dental hygienists, and architects. These occupations are found both up and down in the wage and education structures.

The most prevalent occupations in sequential OILM careers are split between office and industrial contexts, including financial managers, supervisors of several types, and industrial machinery repairers. Occupations having a high propensity to show up in occupational network careers include special education teachers, licensed practical nurses, computer systems analysts and computer programmers. Occupational network careers are typified by workers moving back and forth non-sequentially between two or more clusters of jobs.

The occupations with high prevalence in disorderly careers include proto-typical low-wage, personal service occupations like taxicab drivers, apparel sales workers, baggage porters, and private household cleaners. However, they also include artists, performers, and craft artists, property managers, and interviewers. Artists may be particularly prone to the definition of disorderly careers as they may work in seasonal jobs as they seek to make ends meet while pursuing their creative outputs.

Table 13, Panel A shows the proportion of the longest career sequence by career type using the best-fit approach (V1), and Appendix Table A1 shows the corresponding table for the absolute-level approach (V2). As expected, workers of each orderly career type spent the highest proportion of their work history on average in the corresponding career sequence type. For example, individuals who are classified as having employer careers spend, on average, 0.814 of their work history in their longest employer spell in Table 13, Panel A. Disorderly careers are typified by spending low proportions of their work history in any of the four orderly career spells, which makes intuitive sense given the definition of disorderly careers based on Equation (1). Employer careers have a high degree of occupational spell continuity (0.508) and OILM careers have a relatively high employer (0.459) and occupational continuity (0.446) consistent with the way that most OILMs link relatively long employer and occupation careers. Occupational network careers also have a high degree of occupational continuity, with the longest occupational spell representing 0.464 of the work history.

In Table 13, Panel B, we provide the average proportion of weeks employed, out of the labor force, and unemployed as well as the education, gender, and racial composition of each of the career types for the best-fit (V1) approach.[14] Workers categorized as having employer careers have high levels of time employed (0.741) and correspondingly low levels of time out of the labor force (0.157) and unemployed (0.040). By contrast, while workers in disorderly careers have the largest share of weeks unemployed (0.078) in their work histories, the differences from the occupation (0.057), OILM (0.054), and occ network (0.070) are not as large as may be expected. Similarly, education and gender do not look to be major predictors of career type with the average education level for all types being around 13 years and the gender composition of each type evenly divided near 50-50. This is consistent with Wilensky's (1961) argument that career orderliness is a distinct dimension of social stratification.

In Table 14, we present the results from a multinomial logit model to predict the best-fit (V1) career type based on workers' demographic characteristics and summary measures of career history (e.g. the proportion of their work history unemployed or out of the labor force), with Table A2 presenting the results for the absolute-level (V2) approach. The reference category for the multinomial logit is occupational careers. Women and workers with more education are more likely to have disordered careers (relative to occupational careers). Workers in employer careers spend a significantly lower share of weeks unemployed relative to workers in occupational careers, while workers in employer careers and those in sequential OILM careers are less likely than those with occupational careers to spend time out of the labor force. Finally, the proportion of weeks unemployed is associated with a higher probability of classification into occupational network careers and disordered careers.

[14] Appendix Table A1 panel B provides the results for the absolute level approach (V2).

Table 11c
Comparison of career classification types.

Career Type Version 1 (V1) "Best-fit"	Career Type Version 2 (V2, "Absolute Level").						Total (N)	Column Percent
	Employer	Occupation	Sequential OILM	Occ. Net.	Unclassified	Disordered		
1.Employer	1836	0	51	0	619	0	2506	19.75
2. Occupation	721	1197	147	405	293	0	2763	21.78
3. Sequential OILM	4	137	1231	50	698	0	2120	16.71
4. Occ network	23	157	0	1305	866	0	2351	18.53
5. Disordered	0	33	0	0	1253	1660	2946	23.22
Total (N)	2584	1524	1429	1760	3729	1660	12,686	100
Row Percent	20.37	12.01	11.26	13.87	29.39	13.09	100	

Table 12
Most Prominent Occupations by Career Type (V1, "Best Fit"). Based on the occupations in the longest spell by career type, ranked by the ratio of prevalence to the overall occupational distribution. (Top 200 largest occupations, 1980 3-digit occupational codes).

Employer Career			**Occupation Career**		
Occupation	N	Ratio	***Occupation***	N	Ratio
Postal clerks, except mail carriers	378	3.78	Physicians	357	5.52
Supervisors, distribution, scheduling	131	2.94	Lawyers	430	4.90
Farmers, except horticultural	213	2.83	Dental hygienists	239	4.57
Administrators and officials	167	2.67	Hairdressers and cosmetologists	789	4.23
Electrical power installers and repairers	94	2.52	Firefighting occupations	183	4.02
Supervisors production occupations	441	2.42	Editors and reporters	188	3.54
Industrial machinery repairers	160	2.37	Architects	119	3.35
Firefighting occupations	109	2.24	Registered nurses	1281	3.30
Supervisors, cleaning and building	88	2.20	Police and detectives, public	443	3.17
Purchasing agents and buyers	162	2.19	Mail carriers, postal service	213	3.09
OILM Career			**Occupational Network Career**		
Occupation	N	Ratio	***Occupation***	N	Ratio
Engineers, n.e.c.	210	1.92	Licensed practical nurses	303	3.11
Public relations specialists	92	1.84	Mechanical	78	2.89
Financial managers	330	1.84	Therapists, n.e.c.	67	2.55
Personnel and labor relations	115	1.80	Drywall installers	137	2.51
Heating, air conditioning, and refrigeration mechanics	199	1.74	Clinical laboratory technologists	150	2.38
Industrial	113	1.69	Registered nurses	693	2.34
Administrators and officials	140	1.68	Drafting occupations	113	2.29
Other financial officers	312	1.68	Computer analysts & programmers	374	2.23
Computer systems analysts and	522	1.67	Teachers, special education	81	2.11
Mechanical	82	1.63	Bus, truck, and stationary engineers	81	2.06
Disordered Career					
Occupation			N		Ratio
Sales workers, apparel			155		1.76
Artists, performers, and related			162		1.54
Sales workers, motor vehicles			144		1.50
Sales counter clerks			263		1.47
Personal service occupations			199		1.47
Cashiers			2468		1.47
Mail clerks, except postal service			154		1.46
Clergy			130		1.45
Welfare service aides			199		1.44
Street and door-to-door sales			229		1.44

8. Career types and wages

Identifying career types is an essential step in the broader goal of understanding how labor market structures shape the process of intragenerational job and economic mobility. We now turn to modelling the relationship between these two features of intragenerational mobility by examining the association between career types and: (1) continuous measures of experience and wages/wage growth; and (2) discrete job changes and wages/wage growth in the NLSY data.

Table 13
Descriptive Statistics by Career Type, Version 1 (best fit).

Panel A: Proportion of Work History Spent in Longest Career Sequence, by Career Type				
Career Type	**Employer Sequence**	**Occupational Sequence**	**Sequential OILM**	**Occupational Network**
Employer	0.814	0.508	0.862	0.714
Occupation	0.612	0.781	0.817	0.828
OILM	0.459	0.446	0.944	0.635
Occ Network	0.445	0.464	0.735	0.885
Disordered	0.327	0.334	0.494	0.536
Total	0.532	0.51	0.758	0.71

Panel B. Proportion of Total Work History, by Career Type						
Career Type	Employed	Out of the Labor Force	Unemployed	Education	Female	Black
Employer	0.741	0.157	0.040	13.22	0.485	0.152
Occupation	0.593	0.229	0.057	12.96	0.491	0.163
OILM	0.744	0.161	0.054	13.23	0.454	0.161
Occ Network	0.462	0.285	0.070	12.89	0.416	0.128
Disordered	0.653	0.224	0.078	13.07	0.514	0.163
Total	0.637	0.213	0.06	13.08	0.475	0.154

Table 14
Multinomial logit models of the best-fit career type, NLSY79.

	Best-fit (Version 1) Career type (comparison category: occupational career)			
	Employer	**Sequential OILM**	**Occ. Network**	**Disordered**
Education	−0.0110	0.0210	0.0314*	0.0440***
	(0.0118)	(0.0123)	(0.0127)	(0.0114)
Female	0.149*	0.0594	0.0205	0.205***
	(0.0602)	(0.0628)	(0.0651)	(0.0578)
Race-ethnicity (excluded category: White)	−0.0858	0.00695	−0.129	0.0465
Black	(0.0800)	(0.0825)	(0.0856)	(0.0759)
	−0.0520	−0.0949	−0.312***	−0.0440
Latino	(0.0688)	(0.0714)	(0.0737)	(0.0643)
Proportion of weeks out of the labor force	−1.613***	−1.585***	0.801***	−0.221
	(0.153)	(0.162)	(0.140)	(0.132)
Proportion of weeks unemployed	−4.312***	0.301	3.435***	3.864***
	(0.529)	(0.457)	(0.412)	(0.376)
Constant	0.539**	−0.229	−1.081***	−0.784***
	(0.171)	(0.179)	(0.187)	(0.167)
N	12,161			

Notes: Standard errors in parentheses.
*p < 0.05, **p < 0.01, ***p < 0.001.

8.1. *Career experience and wages*

A mechanism by which orderliness in career types affects wages is through the accumulation of skills and experience within career sequences over time. Our approach complements human capital accounts of how skills affect wages by emphasizing the structures within which experience is accumulated.

Table 15 provides descriptive information on the variables used in the analysis of wages. As noted above, we measure wages based on reports for each job j held by worker i (in occupation A and employer e) during an interview period at time t. In addition to estimating the relationship between wages and the categorical measures of career types presented in Table 11B, we use several measures of within-career work experience to allow for a more gradational test of the effects of different career types on wages over time. First, overall experience (Row 2 of Table 15) is the cumulative work experience in all jobs up to the last week employed in job j at time t. Same-occupation experience is a continuous measure of occupational careers, calculated as the cumulative length of time the worker has spent in occupation A at time t. Firm tenure (in Row 4) is the length of time they have worked at employer e by time t and is also a continuous measure of the current employer career sequence.

Because it traverses multiple employers and occupations, measuring cross-occupation experience is more complicated than calculating firm tenure or occupational experience. We calculated cross-occupation career experience using Equation (2) for worker i working in occupation A at time t:

$$\left(\text{Eq. }2\right)\ \text{cross-occupation career } \exp_{it}^{A} = \sum \theta_{ab} \times \Delta exp_{i(t=j)b}^{a \neq b}, \qquad \text{(Eq. 2)}$$

In Equation (2), for each prior job B in i's work history (and not in occupation A), we multiply the occupational similarity measure θ_{ab}

Table 15
Descriptive information on the 1979–2018 NLSY sample.

#	Variable	Description	Mean	S.D.
1	Wage	Wages, in (inflation adjusted) 2011 dollars	17.02	15.10
2	Overall experience	Work experience, using all jobs in the work history data (in years)	10.98	9.74
3	Same occupation experience	Years of experience in the respondent's current occupation	3.74	5.15
4	Firm tenure	Years of tenure at current firm	3.85	5.64
5	Cross-occupation experience, CPS	Prior experience multiplied by the CPS occupational similarity measure for each occupation in the respondent's work history data. See the text for details	3.50	3.95
6	Cross-occupation experience, O*NET	Prior experience multiplied by O*NET occupational similarity	2.55	3.20
7	Education	Years of education	12.74	2.38
8	Female	Female = 1; Male = 0	0.470	0.499
9	Black	Black = 1; else = 0	0.171	0.377
10	Latino	Latino = 1; else = 0	0.257	0.437
11	Average occupation wage	The average occupational wage, calculated using CPS data from 1992 to 2002	15.37	6.05
12	Proportion weeks working (PW working)	The proportion of weeks in the work history data that the respondent is observed working	0.615	0.271
13	Proportion weeks OLF (PW OLF)	The proportion of weeks out of the labor force	0.230	0.221
14	Proportion weeks unemployed (PW unemployed)	The proportion of weeks unemployed	0.083	0.107
15		Number of unique individuals	12,161	
16		Number of observations[a]	276,979	

Note.
[a] Each observation represents a job recorded in the NLSY work history data for a particular interview period.

between occupations A and B by the work experience in job B between time J and J-1 ($\Delta exp_{i(t=j)b}$). Gathmann and Schönberg (2010) use a similar approach based on occupational similarity to measure the accumulation of task-specific experience across related occupations in Germany. Note that in Equation (2) we exclude same-occupation experience (i.e., cumulative tenure in occupation A), and we refer to the measure as "cross-occupation" career experience to emphasize this.[15] In Equation (2), jobs in the past contribute to the estimate of cross-occupation career experience based on their similarity with the current occupation. Cross-occupation experience based on both the CPS and O*NET measures of occupational similarity θ_{ab} are presented in Table 15.

Finally, we include a measure of non-career experience, that is calculated as total experience minus cross-occupation experience and same-occupation experience. This allows us to test the importance of cross-occupation career experience relative to general work experience accumulated outside of the cross-occupation OILM or network. Non-career experience corresponds to "disorderly" career experience in our approach.

Comparing the effect of non-career experience versus cross-occupation career experience provides a test of the relative influence of prior experience within OILMs or occupational networks on wages. It is important to keep in mind that the occupational similarity measure θ_{ab} is a continuous variable between 0 and 1, so experience in prior occupations will potentially contribute to both career and non-career experience depending upon the level of θ_{ab} between the current occupation A and the prior occupation B.

How does the accumulation of firm, occupation, cross-occupation career experience, and non-career experience affect wages? To answer this question, Table 16 presents models for log wages with individual fixed effects for the NLSY data. This analysis uses all observations of wages for respondents' main jobs between 1979 and 2018. We use all jobs in the work history data in deriving the experience measures.

All the models in Table 16 are fixed effects models of log wages, so unchanging individual characteristics, such as race, gender, or the overall career type drop out of the model unless they are interacted with time-varying variables. Model M1 estimates a baseline human capital model with general work experience, firm tenure, and education as individual level variables. Models M2 and M3 add interaction terms between the different versions of the career type variables and experience, with the excluded category being disorderly careers in both cases. The interaction term tests whether the effect of general work experience varies by career type.[16] In both models, all the "orderly" careers have higher returns to experience than workers in disorderly careers, but there is little difference among the four types of orderly careers. For "unclassified" careers (Row 10 of Model 3), the effect of the interaction term on experience (0.005) is about half that of the orderly career categories.

Models M4 and M5 move from the categorical measures of career type to the continuous measures. In Model M4, we include the four measures of experience: firm tenure, same occupation experience, cross-occupation experience, and non-career experience. In addition, both models include several variables measuring structural features of occupations: the average occupational wage as well as the proportion female (%occfem) and the proportion white (%occwhite) in the occupation. We include interaction terms between %occfem and %occwhite and the respondent's gender and race/ethnicity in rows 23–24. The key finding in Model M4 is that the return

[15] This allows us to differentiate between the effect of same occupation experience and that of different but related occupations based on the occupational similarity measure.
[16] Note that as discussed above with respect to Table 11, career type is a fixed individual characteristic—i.e., a career type is assigned to each person based on their overall pattern of career sequences.

Table 16
Fixed effects models of log wages, NLSY79.

#		M1	M2	M3	M4	M5
		Baseline model	**Categorical Career Measures**		**Continuous Experience-Based Measures**	
			Career type, version 1	**Career type, version 2**	**CPS Cross-occupation Experience**	**O*NET Cross-occupation experience**
1	Cumulative Total Work Experience	0.0347*** (0.00139)	0.0305*** (0.00142)	0.0290*** (0.00147)		
2	Non-Career Experience[a]				0.00928*** (0.00119)	0.0101*** (0.00104)
3	Same occupation experience				0.0274*** (0.000806)	0.0273*** (0.000804)
4	Cross-occupation career experience (CPS)				0.0215*** (0.00111)	
5	Cross-occupation career experience (O*NET)					0.0305*** (0.00134)
	Career type × experience interactions (excluded category: disordered careers)					
6	Employer career x experience		0.00614*** (0.000716)	0.00980*** (0.000880)		
7	Occupational career x experience		0.00675*** (0.000687)	0.00961*** (0.000834)		
8	Sequential OILM career x experience		0.00861*** (0.000656)	0.00937*** (0.000813)		
9	Occ. Network career x experience		0.00687*** (0.000818)	0.0105*** (0.00115)		
10	Unclassified x experience			0.00511*** (0.000681)		
11	Firm tenure	0.0294*** (0.000762)	0.0283*** (0.000761)	0.0289*** (0.000767)	0.0242*** (0.000771)	0.0238*** (0.000767)
12	Education (years)	0.0857*** (0.00192)	0.0851*** (0.00190)	0.0849*** (0.00189)	0.0764*** (0.00168)	0.0740*** (0.00168)
13	Average occupation wage				0.0194*** (0.000381)	0.0198*** (0.000385)
14	Experience squared	−0.000483*** (0.0000174)	−0.000503*** (0.0000175)	−0.000491*** (0.0000177)		
15	Non-Career experience squared				−0.000403*** (0.0000585)	−0.000374*** (0.0000428)
16	Same occupation experience squared				−0.000638*** (0.0000356)	−0.000642*** (0.0000356)
17	Cross-occupation experience (CPS) squared				−0.000622*** (0.0000582)	
18	Cross-occupation experience (O*NET) squared					−0.00121*** (0.0000854)
19	Firm tenure squared	−0.000657*** (0.0000302)	−0.000668*** (0.0000324)	−0.000741*** (0.0000336)	−0.000580*** (0.0000300)	−0.000557*** (0.0000300)
20	Occupation proportion female (% occfem)				−0.0800*** (0.00919)	−0.0590*** (0.00929)
21	Female x %occfem				0.0500*** (0.0123)	0.0373** (0.0123)
22	occupation proportion white (% occwhite)				0.00998 (0.0324)	0.0202 (0.0324)
23	Hispanic x %occwhite				−0.170** (0.0602)	−0.172** (0.0600)
24	Black x occ_white				−0.106* (0.0478)	−0.122* (0.0478)
25	Constant	1.186*** (0.0225)	1.189*** (0.0221)	1.051*** (0.0298)	1.202*** (0.0279)	1.210*** (0.0279)
	N	276979	276979	276979	276729	276729

Note: Standard errors in parentheses.
*p<0.05, **p<0.01, ***p<0.001
[a] Non-career experience is total experience (row 1) minus cross-occupation experience (rows 4 and 5) and same-occupation experience (row 3).

to cross-occupation career experience (0.0215, $p < 0.001$) is about double the rate of non-career experience (0.00928, $p<0.001$).

Model M5 estimates an alternative model that uses the O*NET skill similarity measure (Row 5) to calculate the accumulation of career experience using Equation (2). This variable also has a strong effect (0.0305, $p < 0.001$) and it is about 3-times the size of the effect of skill dissimilar non-career experience (in Row 2). This indicates that the wage benefits of cross-occupation careers are robust

Table 17
Additional variables for wage growth analysis.

Variable name	Description	Mean
5-year age period	Age ranges from 25 to 30, 30–35, 35–40, 45–50, 50–55.	
Period specific career changes:		
Changed firms	Changed firms at least once during the age period	0.528
Changed OILM	Changed OILMs at least once during the age period	0.231
Changed occupation	Changed occupations at least once during the age period	0.628
Changed network career	Changed network careers at least once during the age period	0.427
Wage growth quintile	Quintile of average annual wage growth during a 5-year age range.	2.5
Previous period wage quintile	Quintile of average wages in the previous age period. (1 = lowest, 5 = highest)	2.5

to two separate ways of coding the similarity of occupations.

Overall, the continuous measures of experience in Models M4 and M5 do a better job of explaining wages than the categorical career type measures used in Models M2 and M3. Although classifying workers' work histories into career types (as in Table 11) is useful for highlighting distinct patterns of careers, the continuous measures of experience used in M4 and M5 allow for more nuance in modeling the effect on wages. For example, as discussed above, the measures of cross-occupational experience calculated using Equation (2) allows for a continuous measure of occupational similarity (θ_{ab}) while the corresponding measure of cross-occupation career sequences in Table 3 uses a threshold value of θ_{ab} to define breaks in temporally defined spells. On the other hand, we also note a commonality in the findings: in models M2 and M3, each of the career-type effects in rows 6–9 are roughly equivalent (with the exception of the coefficient of 0.00861 for sequential OILMs in M2)—indicating that there are higher wage returns to experience for workers in orderly careers (regardless of the type) compared to "disorderly" careers. Similarly, in M4 and M5 the returns to the different continuous measures of experience that correspond to specific career sequences (i.e., cross-occupation experience, same occupation experience, and firm tenure) are also roughly equivalent and about 2–3 times larger than the returns to non-career experience.

Our models in Table 16 resemble growth curve models due to the inclusion of interactions of career types and experience. Growth curve models permit the analysis of inequalities in earnings and other job rewards over complete work histories (e.g., Miech et al. (2003); Schulz and Maas (2012); Härkönen et al. (2016); Titma and Roots, 2006). This overcomes a limitation of event history and network models, which typically investigate separate transitions and often lose sight of the complete career line (Rosenfeld, 1992). Our model includes fixed individual effects; a true growth curve model would also have random coefficients for experience.

Growth curve models allow for individual variation in wage growth trajectories by "smoothing" out the complexity of actual career trajectories into individually specific curves. A limitation of this is the assumption that job change has a linear effect (either positive or negative), when in fact the effect of change is contingent upon the context of the origin and destination employers, occupations, and career sequences the worker is moving between. By smoothing over the individual occupational and firm transitions into parameters that characterize a worker's overall life course trajectory, the model attributes to individual characteristics the effects that are due to occupational or labor market structures and career types. This abstracts away from the actual processes of job and career sequences that result in wage growth that can deviate substantially from the smoothed individual trajectories. For example, an individual working for an extended period in a dead-end job (with no wage growth) may experience rapid wage growth upon moving to a different job in a new firm, but a typical growth curve model would miss the sharp discontinuity in wage growth centered around the change in employers. We address this limitation of growth curve models in the next section.

8.2. *Career sequences and variation in wage growth*

Our final analysis examines the effects of career sequence changes on cross-person variation in wage growth, The dependent variable for this analysis is each worker's quintile of wage growth calculated over 5-year intervals. The focus on 5-year quintiles allows us to address our critique of growth curve models at the end of the previous section: growth curve models analyze differences in average rates of long-term wage growth, but they miss the short term and potentially heterogeneous effects of career discontinuity and change. We use the work history data to measure career continuity and variation in wage growth over 5-year age intervals from 25 to 55. Table 17 shows additional variables used in this analysis of wage growth with the NLSY data that we haven't previously discussed. The variables measuring period specific career changes are dummy variables indicating whether a particular change occurred during the age interval. For example, 23.1% of workers changed OILM career sequences during the typical 5-year period, and 52.8% changed firms.

We calculated wage growth as the average annual rate over the period, starting with the first observation of wages closest to the start of the age interval and ending with the last observation of wages closest to the end of the age interval.[17] We use average wage growth over five-year rather than one-year periods in order to better measure the medium-term impact of career stability or

[17] For example, for the 25–30 age range, we start with the first observed wage at 25 and end with wages at 30. If there is no wage observation at 25, we take the closest available one and do the same thing for wages at age 30. In addition, we only use age intervals where there is a difference of 3 to 7 years between the first and last wage observations. We calculate the annual rate of wage growth, using the difference in weeks between the wage observations in the work history data to measure the time difference.

discontinuity over time, as moving to a "good" job might involve not only a difference in starting wages that is observed immediately but also a higher level of subsequent wage growth.[18] Rather than modeling the average rate of wage growth using a linear model, we divide the wage growth into quintiles separately for each age interval, which allows us to measure dispersion in the effects of career changes rather than just the average effect. Table 18 shows the age-specific median rate of wage growth for each quintile. The median rate of growth is 0.027 and 0.129 per year in the middle and fifth quintiles for ages 25–30 and 0.005 and 0.097 in the middle and fifth quintiles for ages 50–55. While the rate of wage growth declines with age, there is substantial variation in growth rates during each age interval. Wage growth is fastest in workers' first 10 years in the labor market consistent with previous research on wage growth over the career (e.g., Bernhardt et al., 2001). In addition to the quintiles of wage growth, we also control for the worker's previous wage level, also measured with quintiles estimated separately for each age interval.

Table 19 shows the results of a multinomial logit model predicting the worker's age-specific quintile of wage growth, with the middle quintile excluded as the comparison category. Using quintiles of wage growth as the dependent variable allows us to shed light on the ambiguous results of differences in wage growth across various types of orderly careers found in Table 16. For example, the results of Table 19 indicate that changing firms has a significant positive effect on the probability of being in both the lowest and highest quintiles of wage growth over the five-year intervals. Unlike the results of Table 16, which finds a positive overall effect of firm tenure on wages (i.e., a positive effect of job stability with the same employer), the results in Table 19 suggest that job stability isn't intrinsically beneficial to wage growth if someone is stuck in a job without access to a firm internal labor market or to competitive external opportunities through an OILM (Riekhoff et al., 2021).

By contrast, changing an OILM increases the probability of being in the first quintile of wage growth, but decreases the probability of being in the highest quintile. Consequently, workers who change firms but stay in the same OILM career sequence (as defined earlier in Table 3) have a higher probability of achieving higher rates of wage growth than workers who stay in the same job. Since OILMs promote wage mobility within and across firms due to the progressive development of skills and knowledge associated with them, OILM-related career stability is beneficial for job quality. On the other hand, we don't find significant net effects of changing occupations or occupational-network career sequences, once we control for OILMs.[19] A possible explanation for this is that these career types are associated with heterogeneous wage-setting processes. As we noted earlier, it is likely that there may be OILMs present in these career sequences, either because our Census categories are too crude to detect them (in the case of occupational career sequences) or we have not identified possible OILMs within our "occupational network" career sequence beyond those described in Table 4. Moreover, our focus on discrete changes in a short time period (5 years) may disadvantage occupational network career sequences, which are likely to be more useful in explaining longer term trends.

9. Conclusions

Spilerman (1977) brought labor market structure—especially as represented by occupational structure— to the forefront in explanations of intragenerational mobility by developing the concept of the "career line" as linking structural aspects of occupations and labor markets to individuals' characteristics and socioeconomic attainments. Research on intragenerational mobility and inequality has made considerable progress since Spilerman's article, though challenges remain. This article addresses two of these challenges: identifying patterns of job mobility; and linking career types and job mobility to wages.

First, we identified different types of careers represented by patterns of attachment to and mobility between occupations and organizations: those that are focused on a particular employer; those centered in a single occupation; and those that span occupations. The latter is the most difficult to conceptualize and measure and we identified occupational linkages in two ways: (1) as representing sequential movement in occupational internal labor markets (OILMs); and (2) as movement among occupational networks.

Second, we used these career types to examine differences in wages and wage growth in five year periods over work histories in the NLSY. We showed that orderly career types are associated with higher wages than disorderly careers, reflecting the greater skills and experience that are accumulated within orderly careers. Our analysis of wage mobility in five-year periods across the life course demonstrates that workers may experience uneven wage growth from period-to-period and that wage progression depends on the labor market structures that define career types: workers experience the largest wage gains when they change firms and remain in the same OILM.

We have addressed these challenges by analyzing intragenerational mobility and complete work histories using aspects of sequence analysis, network models, and growth curve models. From sequence analysis, we see career lines as sequentially ordered (from the individual worker's perspective) based on a temporal series of mobility and immobility between occupations and employers. Unlike sequence analysis that identifies career patterns inductively, however, we first identify ideal type careers and then categorize individual workers' career types based on our typology. Following the network approach, we analyze the aggregate flows between occupations and then examine the logic and continuity in *individual* workers' careers across occupation and employer changes. We use aspects of growth curve models to incorporate measures of work experience derived from the different career types to help explain

[18] To prevent measurement error in wages from affecting the results, we flagged cases with large changes (more than 50%) in wages between observations that were followed by large changes in the opposite direction in the next observation. We linearly interpolated between observations that were flagged as likely due to measurement error. For example, if in three successive observations the wages were 20, 50, and 18, then the second case is flagged as measurement error and a linear interpolation of 19 is substituted instead.

[19] In an alternative model without the firm and OILM changes, the effect of changing occupations increases the probability of being in the lowest two quintiles of wage growth.

Table 18
Quintiles of annual wage growth, by 5-year age period[a].

Age period	1 (lowest)	2	3	4	5 (highest)	Overall
25–30	−0.073	−0.006	0.027	0.063	0.129	0.028
30–35	−0.075	−0.010	0.018	0.051	0.119	0.021
35–40	−0.069	−0.005	0.021	0.052	0.113	0.022
40–45	−0.084	−0.016	0.007	0.034	0.093	0.007
45–50	−0.084	−0.017	0.004	0.027	0.079	0.002
50–55	−0.091	−0.017	0.005	0.031	0.097	0.005
Average	−0.079	−0.012	0.014	0.044	0.107	0.015

[a] The quintile-specific median is in the cells.

Table 19
Multinomial logit models of career stability and wage growth quintile.

	Wage growth quintile (baseline category = 3)			
	1 (lowest)	2	4	5 (highest)
Period specific career changes:				
Changed firms	0.988***	0.263***	0.0676	0.301***
	(0.0394)	(0.0389)	(0.0389)	(0.0395)
Changed OILM	0.381***	0.132*	−0.0942	−0.232***
	(0.0493)	(0.0521)	(0.0535)	(0.0532)
Changed occupation	0.00652	−0.0266	0.0771	−0.0218
	(0.0457)	(0.0442)	(0.0436)	(0.0451)
Changed network career	−0.00120	0.0159	−0.0188	−0.0157
	(0.0459)	(0.0461)	(0.0457)	(0.0468)
Female	0.0597	0.00764	−0.117***	−0.471***
	(0.0326)	(0.0319)	(0.0319)	(0.0328)
Black	0.0694	0.0584	−0.160***	−0.371***
	(0.0468)	(0.0462)	(0.0464)	(0.0480)
Hispanic	−0.130**	−0.0418	−0.0756	−0.00687
	(0.0427)	(0.0422)	(0.0420)	(0.0432)
Education	−0.0746***	−0.0550***	0.0723***	0.188***
	(0.00725)	(0.00713)	(0.00703)	(0.00720)
Previous period wage quintile (excluded category: Third quintile)				
First (lowest)	−0.943***	−0.277***	0.259***	1.378***
	(0.0566)	(0.0522)	(0.0505)	(0.0504)
Second	−0.207***	0.00995	0.203***	0.591***
	(0.0497)	(0.0485)	(0.0483)	(0.0508)
Fourth	0.102*	0.0519	−0.141**	−0.336***
	(0.0476)	(0.0470)	(0.0477)	(0.0529)
Fifth (highest)	0.566***	0.218***	−0.240***	−0.693***
	(0.0494)	(0.0498)	(0.0510)	(0.0567)
Constant	0.422***	0.586***	−0.883***	−2.591***
	(0.101)	(0.0987)	(0.0998)	(0.105)
N	42,897			

Notes: Standard errors in parentheses.
*$p<0.05$,**$p<0.01$,***$p<0.001$.

wage differences among workers. Finally, we use quintiles of wage growth over 5-year intervals of the life course to assess the heterogeneous effects of career changes on the dispersion of wage over time.

Our contributions in this article have several implications for studies of intragenerational mobility. Career types provide a way of linking labor market structures such as occupations and organizations to inequalities in jobs and job rewards. Our perspective emphasizes the importance of labor market structures for explaining mobility and socioeconomic achievement as opposed to assuming that these result from human capital and other individual characteristics. We need to understand better differences among the ordered career types, a goal that requires work history data on both organizations and detailed occupations. We also need analyses of how changes in the orderliness of careers affect upward and downward economic mobility for different cohorts and time periods. This is especially timely in view of the rise of nonstandard work arrangements that are associated with career instability.

Moreover, our emphasis on career continuity is helpful in studying the consequences of a wide range of phenomena for which stability of work is an important explanation. Our distinction between ordered and disordered careers can help explain outcomes in which career continuity and stability play a major role, such as mental health, family dynamics (e.g., the motherhood penalty in wages), social participation, and grievances related to immigration that have helped fuel neo-populist movements.

Intragenerational mobility is a vibrant research area, and we have much left to do. How occupational, organizational, and other labor market structures interact with individual characteristics to generate inequalities in socioeconomic achievement—measured by wages and other indicators of job quality, and distributed unequally by gender, race, age, education, among others—will remain a focus of research on social stratification and inequality far into the future.

CRediT authorship contribution statement

Arne L. Kalleberg: Writing – original draft, Conceptualization. **Ted Mouw:** Methodology, Formal analysis, Data curation, Writing–data and results sections. **Michael A. Schultz:** Writing – review & editing, Methodology.

Appendix

Table A1
Descriptive Statistics by Career Type Version 2 ("absolute level")

Panel A: Proportion of work history spent in longest spell, by type of spell and career type				
Career type	employer spell	occupational spell	sequential OILM	occ network
Employer	0.893	0.650	0.930	0.810
occupation	0.448	0.667	0.729	0.749
Oilm	0.506	0.505	0.991	0.663
occ network	0.514	0.646	0.896	0.975
disordered	0.278	0.291	0.456	0.523
Unclassified	0.447	0.399	0.646	0.631
Total	0.532	0.51	0.758	0.71

Panel B:						
	Proportion of total work history weeks:					
Career Type	employed	out of the labor force	unemployed	Education	Female	Black
employer	0.627	0.199	0.044	12.941	0.492	0.145
occupation	0.717	0.181	0.057	13.577	0.467	0.173
Oilm	0.766	0.145	0.048	13.192	0.442	0.164
occ network	0.412	0.295	0.064	12.565	0.379	0.117
disordered	0.637	0.232	0.086	13.043	0.504	0.164
Unclassified	0.668	0.214	0.065	13.118	0.511	0.161
Total	0.637	0.213	0.060	13.078	0.475	0.154

Table A2
Multinomial logit model of career type version 2 (absolute levels), NLSY79

	Career type (comparison category: occupational career)				
	Employer	Sequential OILM	Occ. network	Disordered	Unclassified
Education	−0.133***	−0.0905***	−0.127***	−0.0393**	−0.0623***
	(0.0137)	(0.0154)	(0.0161)	(0.0149)	(0.0126)
Female	0.0448	0.0302	−0.0505	0.151*	0.151*
	(0.0699)	(0.0789)	(0.0819)	(0.0764)	(0.0651)
Race-ethnicity (excluded category: White)					
Black	−0.359***	−0.159	−0.392***	−0.0958	−0.203*
	(0.0926)	(0.103)	(0.108)	(0.0999)	(0.0850)
Latino	−0.126	−0.171	−0.375***	−0.0772	−0.221**
	(0.0791)	(0.0906)	(0.0928)	(0.0849)	(0.0737)
Proportion of weeks out of the labor force	0.280	−1.140***	1.733***	0.853***	0.569***
	(0.178)	(0.224)	(0.190)	(0.189)	(0.166)
Proportion of weeks unemployed	−4.682***	−2.277***	0.737	3.440***	0.797
	(0.554)	(0.602)	(0.530)	(0.471)	(0.445)
Constant	2.506***	1.507***	1.270***	0.157	1.582***
	(0.201)	(0.226)	(0.236)	(0.223)	(0.188)
N					

Notes: Standard errors in parentheses.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

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