

ESTUDIOS SOBRE LA ECONOMÍA ESPAÑOLA

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EEE 132

Abril 2002



<http://www.fedea.es/hojas/publicado.html>

TEMPORARY HELP AGENCIES AND THE LABOUR MARKET BIOGRAPHY: A SEQUENCE-ORIENTED APPROACH*

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—Version: 2002-04-05—

Abstract

This paper analyzes to what extent Temporary Help Agency (THA) intermediation in the labour contract enhances workers' attachment to the labour market. In particular, we study whether having been enrolled by a THA is related to enjoying a job under a permanent contract at the end of the observation period. For this purpose, micro-level data from the Spanish Social Security records are exploited through the use of a method —called Optimal Matching Analysis— that measures resemblance between sequences of labour market states along time. Results show that THA workers present stronger similarities to sequences of labour market states that finish in permanent contracts. In addition, being a THA worker arises as the key factor among those determining similitude to those states.

Keywords: Optimal matching analysis, labour market attachment, temporary help agencies.

JEL Classification: C49, J60

* This work has benefited from financial support by CICYT SEC99-1191. We would like to express our gratitude to the Spanish Ministry of Labour for providing the database for this research. We are grateful to comments received by seminar participants at Universidad de Alcalá and Universidad de Oviedo.

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1. Introduction

Temporary help agencies —THAs for short¹— are companies that hire temporary workers and send them out to do temporary work on the premises of, and under the supervision of, client firms solicited from the business world. Their key feature is that workers remain on the THA's payroll while working for the client firm: i.e., workers engaged by THAs and placed at the disposal of client firms become a part of the triangular relationship between the worker, the THA and the firm in which the work is performed².

Literature explaining THA work is scant and in general biased towards rejecting this form of labour contracting. Common criticisms are that (1) THA workers only receive brief assignments interspersed with relatively long periods of unemployment (Bronstein, 1991); (2) that not only THA workers are paid less than core workers for working at similar types of jobs, but also that their chance of obtaining employee benefits are less than that for traditional core workers (Emerson, 1988; Moberly, 1987); (3) that such a situation may create uncertainty and greater economic risk for these workers (Blank, 1998); and (4) that extensive reliance on THA workers may create two classes of employees: permanent workers with relatively secure, high-paying employment and THA workers (along with temporary workers in general) who have only sporadic, low-paying work (Mangum et al. 1985).

Indeed, there is an implicit assumption in much of the literature on motivations for employers' reliance on THA-intermediated work that this form of labour contracting serves primarily to buffer firms' core regular employees from changing demand conditions and as a means of cutting per-hour labour costs. Although these demand factors are obviously relevant for discussing the importance in determining the growth of this form of temporary employment, this approach neglects an important complementary point of view: THAs develop a task of screening in order to match the individuals with the most appropriate level of skills to the jobs in question³. It is precisely to this issue that our analysis is addressed. Our goal is to assess empirically the importance of this THA screening role as revealed by how it may be affecting workers' attachment to the labour market.

For this purpose, our focus is placed on analyzing individuals' labour market biography as a whole. We define the "labour market biography" by following closely the Spilerman's concept of a career line: «By a 'career line' or 'job trajectory' we shall mean a *work history* that is common to a portion of the labour force. The focus, therefore, is on a life-cycle phenomenon, typically a sequence of jobs, rather than on the employment situations of individuals at a given time or at a particular age» (Spilerman, 1977). Our concept of labour market biography is also a life-cycle phenomenon; nonetheless, it widens the scope of career: whilst a career is a sequence of jobs, a labour market biography is a sequence of labour market states.

¹ Other frequent names in the literature in order to address to these private intermediaries (especially in the U.S.) are temporary staff agencies, temporary work businesses, temporary services employment agencies or temporary services supply firms.

² This constitutes the main difference with respect to other variants on the use of temporary help like employee "leasing" firms—which have no role in worker recruitment or screening and basically take on the payroll of the existing workforce from (mainly) small firms in order to write the paycheck, pay the taxes, prepare and implement personnel policies and other paperwork— or private employment agencies—which do not directly contract workers and rather limit their operation to only facilitating employment relationships between client workers and firms for a fee charged to either the employer or the employee. For a more detailed analysis on the nature of THAs as intermediaries, see Muñoz-Bullón (1999).

³ It should be clear at the outset that we are not asserting that the above-referred demand-driven factors are unimportant in influencing the growth of this form of labour contracting. Rather, we maintain that the THA screening role is also relevant, judging by its effect on the dynamics of workers' labour market attachment.

The isolation of patterns of labour market biographies can be addressed in our dataset to the extent that it reveals individual's progress over time —measured by the degree of attachment to the labour market. Labour market attachment is defined in this study as the strength of the link to the labour market state, as established by workers' situation at predetermined moments of time, which range from unemployment (or inactivity) to employment through a permanent contract. Data has been obtained from the Spanish Social Security records. Information on the evolution of complete individual work histories are exploited in the second half of the decade of the nineties for two subsamples of workers: the first one is constituted by workers employed sometime by a THA; the second one is composed by no-THA workers, and is taken as a control group. It must be noted that the composition of this second subsample makes it difficult to implement a complete evaluation of the THAs' role, since it only includes individuals nonemployed at the same time period as the ones belonging to the first subsample. That is, the subsample of no-THA individuals excludes those individuals who were on-the-job. As a consequence, an eventual deadweight effect cannot be observed. Despite this constraint, as we will see, there is still much to be learned about attachment from these data. Our main hypothesis is that workers engaged through those intermediaries will have improved chances of enjoying a job under a permanent contract at the end of the observation period. That is, we expect that a job obtained through a THA will not create a disruption in labour market biographies, but the opposite.

Conventionally, the analysis of labour market states is in terms of statistical models—for instance, duration models— built for fitting those transition data. The research objective with such models is precisely the study of the determinants of the transitions observed from one state to another; that is, the technique is especially suitable to examine the effects of a set of covariates on the chances that a particular event will occur (for instance, a transition from unemployment to employment and viceversa). In addition, the focus of the empirical analysis is established on the amount of time that individuals spend in those different states. Those types of models are indeed very powerful in establishing the processes that shape the unfolding of events, and much research has exploited this hazard modelling in order to test economic hypotheses. Unfortunately, although duration models are powerful tools to estimate transition probabilities between states, they do not provide an analysis of the sequence of states taken as a whole.

This is the main reason why we adopt another approach to analyse sequential data, in particular, optimal matching analysis (OMA). Rather than to study the determinants or the timing of a specific transition, we focus on the analysis of labour sequences taken as wholes. As far as we know, in the context of social sciences this sequence-based approach has only been applied in Sociology, mainly for the analysis of careers (Abbot and Hrycak, 1990), and social mobility (Chan, 1994; Halpin and Chan, 1998)⁴. As we will see, exploring the utility of this sequence-oriented approach will be one of the main insights of the paper. It must be underlined that we are not asserting that stochastic analyses are not convenient for predicting the unfolding of career events. In our data, careers unfold in time, and predicting development at any given point in time requires probabilistic modelling: therefore, one may still employ stochastic methods to find the forces producing those patterns. However, our empirical techniques offer complementary information and provide a more convenient method in order to get an overview about the pattern of sequences of labour market states. First, they consider directly the sequence of events as a whole: in this sense, our study should be linked to the determinants of a particular labour market trajectory, rather than to a particular transition. Second, the order in which jobs are taken up is not overlooked, which is an important element of career structure; it may be the case, for instance, that labour market states appear in a certain order, so that some job sequences may be empirically less probable than others. Third, those techniques enable the

⁴ The origin of those empirical techniques (and the related software programmes) is encountered in other sciences as Biology and Natural Science, where the analysis of sequences is long lasting (as in DNA research, for instance).

study of similarities among different sequences, and they do this without imposing restrictive stochastic assumptions to the empirical analysis.

Our main OMA results have found a relationship between THA intermediation and successful labour market biographies, especially for relatively young women. In addition, by following the Blinder/Oaxaca (1973) methodology, we find that being engaged by a THA constitutes the main reason for the gap between THA and no-THA workers' distance to ordered sequences. Therefore, instead of taking our OMA results as input to some additional descriptive analysis—such as is usually done with clustering, scaling or grouping algorithms—we are able to show how individual and job-related characteristics shape the estimated dissimilarity to ordered biographies.

The paper proceeds as follows. Firstly, we briefly review the importance of the concept of career in Sociology and Economics, using the Spilerman's terminology in order to define patterns of labour market biographies. Secondly, we present the data in detail, using a first descriptive analysis of sequences. Thirdly, optimal matching techniques are applied and results obtained are presented. Finally, a conclusions section resumes the main insights of the paper.

2. The conceptual framework

The concept of career has received wide attention both from Sociology and Economics. In Sociology the analysis of careers has a long tradition⁵. At the beginning of this branch of literature in the 50's, and along the first years of the 60's, the career was explicitly conceived as a sequence. However, after those first steps, in the 70's this approach was rapidly changed: some authors analysed careers as individual transitions, leaving aside the perspective of the careers as embedded in the life-cycle⁶. This new line of research included the career in the organizational structure. The difficulties of empirical techniques to manage whole sequences restricted the empirical analysis to single transitions. During this period, the effort to understand careers as sequences was, in Sociology, mainly theoretical. However, along the 80's and the 90's some sociologists—Andrew Abbot constitutes the main example⁷—has applied to Sociology methods for sequence data developed in other sciences. This branch of literature is the main source of empirical techniques for our empirical analysis, and its main utility—as stated in the introduction above—consists of treating a sequence of events directly as a whole.

In Economics, the main reference for careers may be attributed to Sicherman and Galor (1990). However, in segmentation theory Piore (1975) developed a very close concept—the *mobility chain*—which became relevant in order to understand how internal labour markets work, since only workers of the primary sector can have a career. Although in both approaches the theoretical analysis focuses on the different occupations held by individuals along time, they do not provide insightful predictions about the order of the sequence itself.

Anyway, both in Sociology and Economics the usual approach has been to analyse only the sequence of jobs. However, the career is a part of the labour market biography as a whole. Along the labour market trajectory, employment spells are interspersed with unemployment and inactivity periods. Those three main labour market states—inactivity, unemployment, and

⁵ Here, we mainly follow the section I of Abbot and Hrycak (1990).

⁶ Numerous authors have conceptualized careers as a stochastic process and have defined patterns of mobility in terms of transition probabilities between positions. See, for instance, Vroom and MacCrimmon (1968), Forbes (1971), Mahoney and Milkovich (1971), or Gillespie, Leininger and Kahalas (1976). Those authors tend to emphasize the usefulness of conceptualizing career mobility as a Markov chain process.

⁷ Indeed, Abbott (1983) attempted to characterize the theoretical and methodological literature on sequences.

employment— imply different degrees of attachment to the labour market. However, the position at a given moment is an incomplete piece of information on the individual's labour market attachment. Therefore, it is necessary to construct sequences of labour market states in order to learn how strong (or weak) the attachment of an individual is to the labour market.

The labour market biography is precisely the sequence of labour market states along time. Biographies may be observed with different degrees of detail, which will depend both on the quality of the data and on the research aim: we may use a mere sequence of activity and inactivity states or distinguish different types of activity and/or inactivity. That is, mobility can be observed inside those basic labour market states, mainly in the employment category⁸. The strongest degree of attachment corresponds to those spells under a permanent contract, since the link to the labour market is presumably of a long-term nature. A weaker degree of attachment may be assigned to those spells under a temporary contract, since the link is presumed as a short-term one—at least with the current job. Finally, differences may be considered among different temporary contracts, and their degree of attachment to the labour market can, therefore, be analysed.

Following the terminology of Spilerman (1977), we classify the labour market biographies as 'ordered' or 'chaotic'. A biography is defined as 'ordered' when the attachment to the labour market is increasing through the observed sequence of states. Otherwise, the sequence would not increase the individual's attachment to the labour market. Note that temporary contracts along with unemployment or inactivity states in between must not necessarily be considered chaotic: the unemployment spell may be needed to develop a more efficient search for a better job. Strictly speaking, we could properly distinguish 'chaotic' and 'ordered' biographies by exclusively considering labour market biographies along the whole life-cycle. In addition, an ordered biography may be disrupted by a dismissal, consequently creating a 'chaotic' sequence from then on. In short, a 'chaotic' sequence should exhibit a non-unilineal progression (in terms of labour market attachment). Hence, the distinction between 'ordered' and 'chaotic' biographies must be carefully used: we should consider those two types of biographies as extreme cases, with many intermediate situations in between⁹.

With this conceptual framework, we desire to study how the use of a THA affects worker labour market biographies in Spain. The analysis will be presented in terms of more or less ordered biographies, and/or more or less chaotic biographies. In a labour market with vertically-differentiated agents, THAs have a screening role because they only accept workers who are "sufficiently" good. Other things equal, these workers are on average of better quality than no-THA ones, and therefore, likely to achieve a permanent contract more quickly. In addition, positions covered by client firms through THAs are typically "assessment" positions in which performance—visible to a number of higher-level persons in the organization—largely determines future career mobility; therefore, these observations and skill development characteristics of the THA positions are expected to increase the probability that capable people will be engaged to permanent positions. Hiring THA workers to monitor them and then to offer permanent positions only to those who perform well seems to have become a common strategy by employers—see, Blank (1998), Muñoz-Bullón (1999), or Segal and Sullivan (1997).

We then wonder whether ordered biographies are more present among those who have had a job under a temporary contract through a THA. We will consider that an ordered biography

⁸ With some intellectual effort we might distinguish among different types of inactivity or unemployment states, although those differences might not be as clear as the ones between different types of employment states.

⁹ Our definition of labour market biography—see the Introduction section—is very similar to the definition of career used by Wilensky (1961). This author understood the term 'career' as a life plan, and he used 'career' as the contrary of 'disorderly work history'. The latter is a job sequence where the following occupation does not increase job rewards.

ends in a job under a permanent contract (i.e., the state with the greatest attachment to the labour market). Since our research objective is defined in terms of the sequences of states, the analysis of sequences is a useful empirical technique to be applied. Our empirical analysis of the sequences of states will focus on typical patterns and the sequences differences between those who have passed through a temporary employment with a THA and those who have not.

3. Data

Spain provides a useful case study to test the relationship between the THAs and the labour market biography. In Spain THAs were allowed to operate for the first time under regulation provided for by the 1994 labour market reform. Prior to this date, THAs had developed in fairly anarchical conditions, free of the constraints of a well-defined legal framework (for details, vid. Rodríguez-Piñero, 1992 and 1994). During the last five years, the use of THA workers by employers has increased tremendously. As can be seen in Table 1, in Spain the proportion of temporary contracts managed by THAs over the total of temporary contracts registered in the Spanish Public Employment Office —*Instituto Nacional de Empleo*, INEM— has almost multiplied by three between 1995 and 1999. Given that almost 16 percent of all temporary contracts are being managed by THAs, an empirical assessment of how successful these labor market intermediaries are in assigning workers to jobs has important policy implications. Among these contracts, the majority are based on unskilled jobs (59 per cent in 1998). However, the main clients of these firms are not in general badly educated workers: in 1998, the proportion of contracts in THAs for individuals in possession of secondary or higher education was 76 per cent in contrast to a proportion of only 64.7 per cent in the total number of registered contracts¹⁰. Hence, as the THA labour force becomes more numerous and diverse, it is important to explore which economic implications this form of labour contracting may have for workers.

Table 1. Temporary contracts managed by THAs in Spain

Year	Temporary contracts (1)	Temporary contracts through THAs (2)	Proportion $\{(2)/(1)\} * 100$
1995	5,519,350	361,633	6.55%
1996	8,273,175	748,601	9.05%
1997	9,386,084	1,260,524	13.43%
1998	10,692,315	1,707,842	15.97%
1999	12,017,063	1,892,284	15.75%

Data on the labour market careers of Spanish workers has been extracted from the Spanish Social Security files. We have two subsamples from those files: they contain the work history from 1990 until 1999 of, respectively, 9,937 affiliated individuals who were working for a THA at the 31st of December of 1995, and 9,903 affiliated individuals who were non-employed at that same date¹¹. This latter sample is taken as a control group. The original database's total number of records is 301.277. Each record corresponds to the affiliation of an individual to a particular Social Security account and, therefore, represents an employment spell with a particular firm (i.e., a matching).

Apart from the empirical technique used, there are two features of the database that are worth emphasizing. First, we provide a new data source for studying intermediation in the labour market in Spain by making use of the Spanish Social Security records: so far, the lack of studies on labour market intermediation is largely due to the absence of accurate data bases on

¹⁰ Similarly, for the U.S. labour market, Segal (1996) finds that personnel supply services workers are more educated, on average, than other hourly workers.

¹¹ As in this data base we cannot distinguish between unemployment and out of the labour force, we address these spells as “non-employment”, given that the information we have is just that these workers are not employed at this time.

employment histories for workers; our database contains a better employment history than any other longitudinal survey of comparable length, since it allows us to determine job and non-employment durations precisely and collects information on all jobs held. Second, we focus on the major output of temporary help agencies, the employment history of their workers, in order to understand the implications of this type of labour contracting.

For each incumbency, data provided includes information about age and gender of the workers, professional category of the worker's contribution to the Social Security, dates when the employment spell starts and ends, type of Social Security system for the worker, the reasons for the termination of the spell (voluntary quit, dismissal or retirement), the Spanish province where the employment spell took place, an identifier indicating whether or not each employment spell is accomplished through a THA, another indicator identifying whether the spell is accomplished through a public employer, and, finally, the type of contract the worker is holding (temporary or permanent).

Inclusion in the present study required, firstly, that workers' career be completely known; therefore, we eliminate incomplete records, and keep only workers affiliated to the General System (*Régimen General*) in order to avoid the bias that special systems like Agriculture, Fisheries, and so on would provoke. In addition we erase the employment history of individuals who belonged to the no-THA subsample and had experienced sometime employment in a THA during the period analyzed, in order to be sure of comparing two groups of individuals actually different from each other. Finally, as THAs were not allowed to operate until 1994 and their performance was not very relevant until two years later, we have further reduced the sample by restricting our analysis to the period 1996-1999. The final sample contains the employment history of 4,370 individuals (2,788 THA workers, and 1,582 no-THA individuals). Table 2 summarizes the sample composition by gender and age, measuring the latter variable at the first time moment of the sequence.

Table 2. Sample Composition

	THA Workers		No THA Workers	
	Men	Women	Men	Women
Initial Age ≤ 35	1,098	1,136	432	359
Initial Age > 35	322	232	539	252
TOTAL	1,420	1,368	971	611

Sequence data—which are inherently discrete—on individuals' labour market states can easily be sampled at intervals from the employment and non-employment spells which constitute the individuals' work history along the period 1996-1999. All that is required is that states are clearly defined and that we have a rule for telling which state a person is at each moment of time. In our application, this involves developing a useful classification of different *degrees* of labor market attachment¹². To do this in a practical way, we created a number of dummy variables, each indicating whether an individual belonged to a particular state at a particular time point. The resulting variable is interpreted as a measure of the individual's labour market attachment (or link) under the different states: inactivity/unemployment (denoted by 1); employment under a temporary contract (2); employment under a temporary contract obtained through a THA (3); and employment under a permanent contract (4). This information is summarized in an ordinal variable showed in Table 3. Each worker's biography can thus be expressed as a sequence of eight labour market states, using a six months basis as the basic time interval. The assigned numbers only indicate the degree of the attachment. For instance, the value 4 means that the attachment to the labour market is bigger than that for value 2, though,

¹² As it is well-known, very complex element schemes may retain important substantive information, but they also increase the computational intensity of the analyses, and may make it difficult to identify similar sequential patterns; conversely, overly simple schemes may disguise meaningful variation in sequential pattern.

of course, not exactly twice as much. A transition from one state to another is defined as a change in this variable. As we do not want to ex-ante impose individuals under a THA temporary contract to enjoy a greater degree of attachment than individuals under any other temporary contract, we have also considered definition B of attachment. In definition B, we do not consider—in terms of attachment—THA-temporary contracts to be different from the remainder ones. This issue is relevant since it affects the sequence as a whole. For example, using definition A the sequences ‘11121234’ and ‘11121224’ are different, but not under definition B (both would be represented by the sequence ‘11121223’).

Table 3
Coding of Labour Market Attachment

DEFINITION A		DEFINITION B	
Coding	Description	Value	Description
1	Unemployed or inactive	1	Unemployed or inactive
2	Temporarily employed	2	Temporarily employed (THA or not)
3	Temporarily employed through a THA	3	Permanent contract
4	Permanent contract		

4. Descriptive Sequence Analysis

Table 4 shows the empirical distribution of states. The non-employment state at the first moment accounts for most observations in all groups. The relative presence of this state declines until an increase is observed in the last time periods. This rise is higher for the THA subsample. A very different trend is observed for the permanent contract state: a extremely low presence at the first moment, but increasing from then on. Comparing both subsamples, initially for all groups, non-employment is more frequent in the no-THA subsample (especially for women), while the presence of the permanent contract state achieves its maximum at the 7th moment for the THA subsample (especially for women).

Table 5 summarizes the main findings of the descriptive analysis on employment status sequences for each subgroup of workers.¹³ Several regularities are immediately apparent in the data. Irrespective of its length, the most frequent sequence is the one represented by a starting stay in non-employment. For men, the mode shows an important presence of the permanent contract state for THA workers, while this state is less relevant for no-THA individuals (both below and above 35 years-old). Moreover, the modes indicate that non-employment is more frequent in the no-THA subsample. For women, the mode for eight-element sequences always correspond to non-employment biographies. However, there is a great discrepancy in medians. In particular, the median biography is more ordered for women in the no-THA subsample. Therefore, this simple descriptive analysis of sequences shows that biographies differ widely by gender; but, inside the same subsample, sequences do not differ so much by age. In addition, modal and median biographies of men and women of the THA subsample are more homogeneous than in the no-THA subsample.

5. Optimal Matching Analysis

As stated in Section 2 above, in this section we make use of a technique so-called *optimal matching analysis* (OMA). With this method, one can search for some interesting patterns in each sequence separately; or one can compare all sequences in a given sample. In any case, a proximity or distance measure is needed to assess either the similarity or dissimilarity of sequences, or of sequences with some pattern. This technique does not directly answer questions about sequence pattern; rather, they generate interval-level measures of resemblance

¹³ This is a straightforward tool for studying labour market attachment: since we dispose of a set of discrete events, we can write down all of their logical combinations and then count the frequency of their occurrence in each sample (Berger, Steinmuller and Ziegler, 1993, and Hogan, 1978).

between sequences¹⁴. Finally, it must be considered to constitute a complementary strategy (but not a substitute) to regression models: while regression models for events aim to describe the evolution of sequences by focusing on transitions, one can try to describe whole sequences. This is precisely our aim in this section.

Table 4. Continuum of Labour Market States

THA Workers								
	% Observations in Time Periods:							
Men, Initial Age≤35								
Coding	1	2	3	4	5	6	7	8
1	92.53	51.91	38.71	29.42	23.68	18.49	27.96	53.10
2	4.10	29.14	37.89	48.00	47.09	47.45	41.35	23.22
3	2.73	15.94	16.94	13.11	12.11	8.65	4.92	1.73
4	0.64	3.01	6.47	9.47	17.12	25.41	25.77	21.95
Men, Initial Age>35								
Coding								
1	95.03	55.28	37.89	30.43	22.36	17.08	24.84	50.62
2	2.80	21.74	31.99	36.34	36.34	38.20	36.02	19.88
3	1.55	15.84	16.77	14.91	17.70	17.08	9.32	3.73
4	0.62	7.14	13.35	18.32	23.60	27.64	29.81	25.78
Women, Initial Age≤35								
Coding								
1	91.81	54.23	40.32	33.36	27.02	21.83	36.00	57.66
2	3.35	23.06	31.95	37.94	37.24	36.62	29.84	15.93
3	4.58	18.49	18.93	15.23	12.24	9.86	4.67	1.50
4	0.26	4.23	8.80	13.47	25.30	31.69	29.49	24.91
Women, Initial Age >35								
Coding								
1	91.81	60.78	46.55	41.38	29.31	25.86	40.09	61.64
2	3.88	19.83	27.16	30.60	31.03	33.62	30.60	15.95
3	3.88	14.66	20.26	16.81	19.83	13.36	6.47	1.72
4	0.43	4.74	6.03	11.21	19.83	27.16	22.84	20.69
No-THA Workers								
Men, Initial Age≤35	1	2	3	4	5	6	7	8
Coding								
1	96.30	65.05	54.86	39.35	35.42	27.08	27.55	41.94
2	3.24	32.41	40.97	52.08	49.54	52.31	50.23	37.27
4	0.46	2.55	4.17	8.56	15.05	20.60	22.22	21.30
Men, Initial Age>35								
Coding								
1	96.85	68.09	59.37	43.97	37.29	28.76	26.16	36.36
2	2.60	28.57	33.58	45.08	47.12	49.91	49.17	41.19
4	0.56	3.34	7.05	10.95	15.58	21.34	24.68	22.45
Women, Initial Age≤35								
Coding								
1	97.77	76.32	61.56	46.80	45.68	39.00	34.82	43.45
2	2.23	20.33	34.26	44.85	40.67	41.50	39.00	30.36
4	-	3.34	4.18	8.36	13.65	19.50	26.18	26.18
Women, Initial Age >35								
Coding								
1	97.22	77.78	65.87	56.35	48.02	40.48	37.70	41.27
2	1.98	20.63	29.76	35.71	39.68	40.48	40.08	37.70
4	0.79	1.59	4.37	7.94	12.30	19.05	22.22	21.03

¹⁴ These measures, taken over a sequence data, can then be taken as input to clustering, scaling or grouping algorithms, which in turn generate information on typical patterns of sequences.

Table 5: Medians and modes of employment status sequences

THA Workers					No THA Workers				
Men, Initial Age ≤ 35					Men, Initial Age ≤ 35				
Length	Median		Mode		Length	Median		Mode	
	Seq.	%(Cum.)	Seq.	%		Seq.	%(Cum.)	Seq.	%
2	11	50.36	11	50.36	2	11	65.05	11	65.05
	12	75.32	12	24.95		12	94.21	12	94.21
3	113	47.36	111	30.51	3	111	49.07	111	49.07
	114	50.36	122	21.22		112	63.89	122	23.15
4	1134	47.36	1222	19.95	4	1121	49.07	1111	34.49
	1144	50.36	1111	19.67		1122	50.93	1222	21.06
5	11344	47.36	12222	16.21	5	11144	49.07	11111	25.46
	11444	50.36	11111	13.11		11211	50.00	12222	18.75
6	113444	47.36	122222	13.21	6	112111	49.77	111111	17.59
	114444	50.36	111111	8.47		112112	50.00	122222	15.05
7	1144441	48.82	1222222	11.48	7	1121112	49.77	1222222	13.89
	1144444	50.36	1111111	5.92		1121122	50.00	1111111	12.73
8	11444411	49.18	12222222	6.01	8	11211121	49.77	11111111	10.88
	11444444	50.36	11111111	5.92		11211222	50.00	12222222	7.87
			[12224444]	[2.37]				[12222444]	[2.31]
			[12222444]	[1.91]				[11114444]	[2.08]
Men, Initial Age >35					Men, Initial Age >35				
2	11	54.97	11	54.97	2	11	67.72	11	67.72
	12	73.29	12	18.32		12	93.88	12	93.88
3	113	49.38	111	33.54	3	111	54.73	111	54.73
	114	54.97	122	16.77		112	64.56	122	21.52
4	1134	49.38	1111	23.29	4	1111	40.82	1111	40.82
	1144	54.97	1222	15.53		1112	52.69	1222	19.67
5	11344	49.38	11111	15.22	5	11121	43.41	11111	30.24
	11444	54.97	12222	14.60		11122	51.39	12222	17.81
6	114442	49.67	122222	13.04	6	111221	44.16	111111	20.59
	114444	54.97	111111	9.63		111222	51.21	122222	16.14
7	1144422	49.69	1222222	12.42	7	1112221	44.90	1222222	14.10
	1144444	50.93	1111111	5.59		1112222	50.83	1111111	13.73
8	11444221	49.69	12222222	6.52	8	11122221	46.94	12222222	9.28
	11444411	50.93	12222221	5.90		11122222	50.83	11111111	7.98
			11111111	5.59				[11444444]	[2.04]
			14444444	4.04				[14444444]	[2.04]
			11444444	3.73					
Women, Initial Age ≤ 35					Women, Initial Age ≤ 35				
2	11	52.38	11	52.38	2	11	77.78	11	77.78
	12	71.39	12	19.01		12	96.43	12	18.65
3	113	48.68	111	31.87	3	111	62.70	111	62.70
	114	52.38	122	15.67		112	75.79	122	15.80
4	1134	48.68	1111	23.33	4	1111	52.38	1111	52.38
	1144	52.38	1222	13.91		1112	61.51	1222	13.10
5	11441	48.77	11111	15.93	5	11111	43.65	11111	43.65
	11444	52.38	12222	12.06		11112	50.00	12222	12.30
6	114411	48.77	111111	10.92	6	111122	48.81	111111	34.52
	114444	52.38	122222	9.60		111124	50.00	122222	10.71
7	1144111	48.77	1111111	7.39	7	1111224	48.81	1111111	27.78
	1144441	50.88	1222222	7.13		1111244	50.00	1222222	28.73
8	11441111	48.77	11111111	7.39	8	11112244	48.81	11111111	21.03
	11444411	50.88	12222221	3.61		11112444	50.00	11222222	5.56
			12222222	3.52				12222222	5.16
			[11444444]	[1.41]				[12222244]	[1.59]
			[12224444]	[1.32]				[11444444]	[1.19]
			[12222244]	[1.14]				[12222444]	[1.19]
								[12244444]	[1.19]
Women, Initial Age >35					Women, Initial Age >35				
2	11	58.19	11	58.19	2	11	77.78	11	77.78
	12	75.43	12	17.24		12	96.43	12	18.65
3	112	49.57	111	42.67	3	111	62.70	111	62.70
	113	57.33	122	15.09		112	75.79	122	15.08
4	1123	49.57	1111	30.60	4	1111	52.38	1111	52.38
	1131	53.88	1222	12.93		1112	61.51	1222	13.10
5	11233	49.57	11111	21.98	5	11111	43.65	11111	43.65
	11312	50.43	12222	11.21		11112	50.00	12222	12.30
6	112333	49.57	111111	15.09	6	111122	48.81	111111	34.52
	113122	50.00	122222	10.34		111124	50.00	122222	10.71
7	1123332	49.57	1111111	10.78	7	1111224	48.81	1111111	27.78
	1131222	50.00	1222222	8.62		1111244	50.00	1222222	7.14
8	11233321	49.57	11111111	10.78	8	11112244	48.81	11111111	21.03
	11312221	50.00	12222222	5.60		11112444	50.00	11111112	6.75
			[11144444]	[2.59]				11222222	5.56
			[14444444]	[2.16]				12222222	5.16
			[12224444]	[1.19]				[11111444]	[1.98]
								[11114444]	[1.98]
								[12222444]	[1.59]
								[12244444]	[1.19]

5.1. Background: The Basics of Optimal Matching Analysis (OMA)

Let us briefly make a comment on the intuitive idea underlying this process of *optimal matching*¹⁵. We consider sequences of states which are elements of a finite space state, say $\mathbf{Y}$. $\mathcal{S}$ denotes the set of all finite sequences over $\mathbf{Y}$, meaning that:

$$\text{if } a \in \mathcal{S} \text{ then } a = (a_1, \dots, a_n) \text{ with } a_1, \dots, a_n \in \mathbf{Y}$$

$n = |a|$ is the length of the sequence. We desire to compare two sequences $a, b \in \mathcal{S}$. The basic idea is to define a set of elementary operations which can be used sequentially to transform one sequence until it becomes equal to the other sequence.

Let $\mathbf{Z}$ denote the set of basic operations and $a(w)$ the sequence resulting from a by applying the operation $w \in \mathbf{Z}$. We consider three elementary operations:

- a) Insertion: $a(i)$ denotes the sequence resulting from $a \in \mathcal{S}$ by inserting one new element (a state from $\mathbf{Y}$) into the sequence a .
- b) Deletion: $a(d)$ denotes the sequence resulting from a by deleting one element from this sequence.
- c) Substitution: $a(s)$ denotes the sequence resulting from a by changing one of its elements into another state.

We can think of sequentially applying elementary operations to a given sequence. Let $a(w_1, w_2, \dots, w_k)$ denote the new sequence resulting from a by applying first the elementary operation w_1 , then w_2 , and so on until finally w_k . Then, given two sequences, $a, b \in \mathcal{S}$, we can ask for a sequence of elementary operations which transform a into b .

In general, there will be many such sequences of elementary operations which transform a into b . Now, the intuitive idea for developing a distance measure for sequences is to look for the shortest sequence of elementary operations which transform a into b . A slightly more general approach is to evaluate the elementary operations by introducing $c(w)$ as the cost of applying the elementary operation $w \in \mathbf{Z}$. We will assume that $c(w)$ is between 0 and infinite. The cost of applying a sequence of elementary operations will be denoted by:

$$c[w_1, w_2, \dots, w_k] = \sum_{i=1}^k c[w_i] \quad (1)$$

Setting $c[] = 0$ for no operation, we can formally define:

$$d_Z(a, b) = \min \{c[w_1, w_2, \dots, w_k] \mid b = a[w_1, w_2, \dots, w_k], w_i \in \mathbf{Z}, k \geq 0\} \quad (2)$$

to measure the distance between the sequences a and b . This measure is by definition non-negative, and $d_Z(a, b) = 0$ only if $a = b$.¹⁶

“*Optimal matching*” without further qualification normally means referring to this distance measure based on $\mathbf{Z} = \{i, d, s\}$ resulting in a metric distance. Of course, the distance measure also depends on the definition of the cost functions $c[w]$. These cost functions can be arbitrarily defined (as we will see below) with respect to the intended applications. As a special case, one can set:

$$c(i) = c(d) = 1, \text{ and } c(s) = 2 \quad (3)$$

¹⁵ Appendix B gives a full account of the mathematical algorithm used by optimal matching.

¹⁶ Symmetry does not automatically hold, but can be forced by equating insertion and deletion costs, or by a slightly different definition: minimum cost of transforming a into b or b into a . Whether the distance measure will also be transitive, and thus constitutes a metric distance, depends on the definition of the set of elementary operations, $\mathbf{Z}$. Transitivity is automatically guaranteed for the simple case when there are only insertions, deletions and substitutions.

The distance between two sequences a and b is then simply the number of indel operations (insertions and deletions) which are necessary to transform one sequence into the other. Once the costs of those three basic operations are established, the algorithm evaluates all possible solutions for each pair of sequences and returns the cost of the most efficient transformation path as the “distance” between the sequences. Pairs of sequences with small “distances” are similar to one another, while pairs with larger “distances” are more distinct.

An example that will show how this optimal alignment method uses the set of operations to align and transform pairs of sequences is the following. Consider two hypothetical sequences:

POSITION	<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	<u>5</u>	<u>6</u>	<u>7</u>	<u>8</u>	<u>9</u>	<u>10</u>	<u>11</u>	<u>12</u>	<u>13</u>	<u>14</u>	<u>15</u>	<u>16</u>
Sequence 1:	4	4	4	4	5	5	5	5	6	6	6	6	6	1	1	1
Sequence 2:	3	3	3	3	3	3	5	5	5	1	6	6	6	6	1	1

In the comparison of Sequences 1 and 2, we find discrepancies in elements 1-6, 9-11, and 14. We could use a transformation that entails a series of substitutions. This would involve, for instance, substituting the 3 3 3 3 in elements 1-4 of the second sequence for the 4 4 4 4 in the first sequence, along with other substitutions later in the sequence. The cost of each individual transformation (e.g., substituting a 3 for 4 in the second element) is set by a-priori established costs of the different transformation operations. If we imagine that the cost of substituting one element for another is the difference in their numeric values ($w(a_i, a_j) = |a_i - a_j|$) then the minimum total cost of aligning the sequences is simply the sum of the individual operations; here, the “distance” between the sequences would equal: $(4*|3-4|)+(|3-5|)+(|5-6|)+(|1-6|)+(|6-1|)=17$.

The algorithm could also conceivably try a transformation strategy that involves insertions, deletions and substitutions. In this comparison, we could delete the 1 in element 14 of Sequence 1, shift the remaining 13 elements one position to the right and then insert a 3 in the first element:

POSITION	<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	<u>5</u>	<u>6</u>	<u>7</u>	<u>8</u>	<u>9</u>	<u>10</u>	<u>11</u>	<u>12</u>	<u>13</u>	<u>14</u>	<u>15</u>	<u>16</u>
Sequence 1:	4	4	4	4	5	5	5	5	6	6	6	6	6	1	1	1
	(original)															
Sequence 1a:	3	4	4	4	4	5	5	5	5	6	6	6	6	6	1	1
	(after insertion and deletion)															
Sequence 2:	3	3	3	3	3	3	5	5	5	1	6	6	6	6	1	1

After the insertion and deletion, we have a situation where Sequence 1a and Sequence 2 are mismatched at only elements 2-5 and 10, thus requiring fewer substitutions. However, if the cost of using an insertion or deletion is high in part because we are adding essentially unknown elements to an established sequence, then using a combination of insertions, deletions, and substitutions is likely to produce a less cost-efficient transformation¹⁷. Let’s say that the cost of insertions or deletion (i.e., indel cost) in this example is 9. The distance between Sequences 1 and 2 using a combination of indels and substitutions would equal $(2*9)+(4*|3-4|)+(|1-6|)=27$. In this case, the most efficient transformation involves only substitutions, though there are instances where simple insertions or deletions can result in the most cost-efficient path of transforming two sequences of equal length.

5.2. Spanish Workers’ Dissimilarities in Labour Market Trajectories

Our method for analyzing the employment histories of Spanish THA and no-THA workers involves a series of steps.

¹⁷ In many applications, the cost of insertions and deletions are fixed at a value slightly higher than the highest substitution cost (see Abbott and Hrycak, 1990)

The first task is to establish the parameters for the optimal matching algorithm (in particular, the substitution costs between several types of labour market states). This step is integral to the matching process, since the cost of the transformation determines the quantitative resemblance between pairs of sequences. Ideally, these costs reflect a combination of the researcher's theoretical assumptions about the inherent distinctions between the states and an empirical assessment of the differences between the states in sequence elements. In applications such as ours, where there are no accepted measures of quantitative differences between types of places to guide the estimation of the costs of substituting labor market states (e.g., unemployment for temporary employment), researchers must rely on their own theoretical assumptions and whatever empirical data are available to facilitate this process. This will allow us to test whether or not the calculated distances are substantially affected by different measures of substitutions costs, and, correspondingly, to learn if our method behaves robustly with respect to variation in those costs; then, results will be described (Section 5.2.1).

Once the cost scheme is established, the optimal alignment algorithm is used to compute the dissimilarities between all pairs of sequences. Since computation time increases exponentially with the size of the sample, subgroups of sequences are drawn taking into account individuals' age and sex. Therefore, the algorithm compares each pair of sequences within these subgroups (Section 5.2.2).

Finally, we again use the results obtained from optimal matching algorithm, this time to find the determinants of the differences in optimal distances to ordered sequences across the THA and the no-THA subsample. The empirical challenge is to go beyond the descriptive analysis provided by OMA and to distinguish how much of the difference in optimal distances across both subsamples can be explained by the impact of individual characteristics and that of having experienced a spell through a THA. For this purpose, we will apply to our analysis the Blinder/Oaxaca (1973) methodology frequently used to estimate discriminatory wage differentials in the literature (Section 5.2.3).

5.2.1. Optimal Matching Parameters: Substitution Costs

Insertion and deletion costs are always identical in the algorithm used in this paper—which is described in the Appendix—and called *indel cost*¹⁸. However, the setting of substitution costs between sequence elements—i.e., the different labour market states—involves, in general, serious consideration of theoretical questions. Optimal matching requires an explicit parameterization of substitutions, since substitution costs may affect distances.

One can use a *default cost function* where indel cost equals 1 and substitution cost equals 2. In this case, the alignment of two sequences provides, then, the longest common subsequence¹⁹.

This option is an interesting starting point because it makes a substitution equivalent to two indel operations—a deletion followed by an insertion; that is, both cost the same. However, we consider that, in our case, the initial basis for setting those costs should be related to the relative importance of changing the labour market states along the job history of the individual. Even though the data shows numerous moves across labour market states in the period of observation some labour market moves involve a substantial change in the degree of attachment to the

¹⁸ Insertion and deletion costs may themselves vary. However, these costs are in some sense a function of what the sequence already looks like; because of this uncertainty, most applications make indel costs the same in all cases (see Abott and Hrycak, 1990, pp. 155).

¹⁹ The relationship is as follows: $\text{length of longest common subsequence} = 0.5 * (m + n - d(a, b))$, where $d(a, b)$ is the optimal matching distance when using the cost functions as indicated in the text; m and n denote the length of the first and second sequence, respectively.

labour market, when compared to other types of changes. That is, some pair of states seem to be fairly closely connected by career mobility than others. It seems necessary, therefore, to add mobility information to our measures of state resemblance or dissimilarity.

In order to do that, we adopted a two-folded approach, which involved the use of two different “distance” matrices. For the first of those matrices, substitution costs is calculated as the absolute difference $w(a_i, a_j) = |a_i - a_j|$; the underlying assumption for this is based on the fact that it is desirable that two states are more similar the less drastic the associated change between the correspondent labour market states. That is, not all substitutions really “cost” the same. The difference between a state of unemployment and a situation of employment through an open-ended contract is greater than the difference between unemployment and a temporary contract. This is why we must differentiate the costs of substitution. Careers involving state changes characterized by low “vertical” distances across occupations will then be linked closely by the matching algorithms. Therefore, this assignment of substitution costs reflects the relative importance —as regards the labour market attachment— when changing the labour market state. The use of definitions A and B proposed in Table 3 is meaningful for this approach. Definition A assumes a positive distance between a temporary contract through a THA and other temporary contract, whilst definition B neglects this assumption.

For our application, it is also worthwhile to derive substitution costs from the frequency of transitions in the given sequence data; with this option, mobility is therefore added to our measure of job resemblance by making use of data-based substitution costs. This involved producing a “distance” matrix —in fact, the third distance matrix used in our empirical analysis— based on mobility information by creating a matrix of transitions between the different values of the labour market states (as defined in Table 3). To explain this idea, let us assume a sample of $i=1, \dots, n$ sequences: $y_i = (y_{i1}, y_{i2}, \dots, y_{iT})$, where the elements are valid states in the state space $\mathbf{Y} = \{1, \dots, q\}$. We can then define:

$$N_t(x) = \text{Number of sequences being in state } x \text{ at } t \quad (4)$$

$$N_{t,t'}(x, y) = \text{Number of sequences being in state } x \text{ at } t \text{ and in state } y \text{ at } t' \quad (5)$$

Those quantities can be used to construct the referred substitution cost matrix; the underlying intuition is that two states are less different when there are, in the dataset, more transitions from one state into the other. One way of using this information about transitions would be to use:

$$p(x, y) = \frac{\sum_{t=1}^{T-1} N_{t,t+1}(x, y)}{\sum_{t=1}^{T-1} N_t(x)} \quad (6)$$

in order to define substitution costs as follows:

$$w(a_i, b_j) = 2 - p(a_i, b_j) - p(b_j, a_i) \text{ if } a_i \neq b_j \quad (7)$$

$$w(a_i, b_j) = 0 \text{ if } a_i = b_j \quad (8)$$

That is, the information on substitution costs is implemented through a matrix of transitions which classifies every move in the individuals’ labour market careers. Since this substitution cost matrix must be symmetric, we then symmetrized this matrix by adding corresponding elements (i.e., the i,j th and the j,i th for all i and j) and replacing both the i,j th and the j,i th with this sum. Finally, since transition figures rise with mobility closeness rather than with distance (i.e., cost), we turned the matrix into a dissimilarity matrix by subtracting each element from a constant. Then, $0 < w(a_i, b_j) < 2$, and substitution cost directly reflects the cumulated transitions

across states. If there are many transitions from a_i to b_j (both directions), the substitution cost will be low, and vice versa.

5.2.2. Results

Given a model of substitution costs, we can apply the optimal matching algorithm to our data. Pairwise comparison of n sequences requires $n(n-1)/2$ alignments. If n is big—as is in our dataset—the computational burden becomes prohibitive²⁰.

We were able to circumvent this problem by taking into account the basic aim pursued with our research. Since our focus is on analyzing the influence of working through a Temporary Help Agency on the degree of individuals' labour market attachment, it makes sense to compare all sequences present in each of the two subsamples described in Section 3 above—the THA and the no-THA subsample—with only a set of predefined sequences. Those predefined sequences correspond to the job histories that, for each subsample, end in a permanent contract along the period of observation (i.e., those sequences that, either in the THA subsample or in the non-THA subsample, show a state value equal to '4' in the last moment). This approach is reasonable, since this set of sequences constitutes our “target” sequences to be used for comparison.

The detailed procedure was as follows. We firstly identified which sequences finished in a permanent contract in the total sample²¹. The three different measures of substitution costs defined in the previous section are used in order to optimally compare all sequences of each subsample—THA group and non-THA group—with each of those predefined sequences²².

Since our aim is to learn whether or not we may expect THA workers to have better opportunities for access to permanent contracts than no-THA ones, we then computed the mean dissimilarity that each individual in those two groups may expect with respect to the set of predefined sequences; finally, the average individual dissimilarity is computed across the individuals in each group. This final value is showed in Table 6 for each of the distance matrices used—named 'Default', 'Absolute Value' or 'Data-Based'.

Results are presented by gender and age, comparing THA and no-THA subsamples. Apart from the dissimilarity index, a means contrast is reported in the last column of those tables, in order to statistically check the differences by subsample. First of all, the results on the optimal dissimilarity measure remain, in general, qualitatively the same across the different substitution cost matrices²³. The most persistent result—across substitution cost matrices—consists of no-THA women with or below 35 years-old presenting a significant larger dissimilarity measure than THA similar women: this dissimilarity is between 2 and 6 percent higher for these individuals. In addition, when the absolute value matrix is used, THA men also show a

²⁰ This occurs in particular with long sequences, since computing time is approximately proportional to the square of the sequence length.

²¹ A table containing all sequences finishing in a permanent contract can be obtained from authors upon request.

²² In every of those cases, indel cost equals 1. In addition, it must be taken into account that the no-THA group can only be compared to those sequences that in Table 4 do not show the state value '3', since no substitution cost can be defined for transitions from and to this state value '3'.

²³ This robustness of the results with respect to different cost matrices was expected, given the experimental work by Forrest and Abbot (1990) who, in other empirical context, indicate the substantial robustness with respect to substitution costs.

significant lower dissimilarity measure than no-THA men. For the remainder groups, OMA shows average dissimilarity measures greater for the no-THA subsample²⁴.

Table 6
Average optimal matching dissimilarity measure to sequences ending in permanent contract

Substitution cost matrix:	AVERAGE DISSIMILARITY MEASURE		
DEFAULT (Definition A)	THA workers	No-THA workers	T-statistic
Men, Initial Age≤35	8.9075	9.0011	-0.8372
Men, Initial Age>35	9.0638	8.8886	1.2576
OVERALL	8.9429	8.9386	0.0533
Women, Initial Age≤35	9.1412	9.3033	-1.3056*
Women, Initial Age>35	9.4184	9.3196	0.5395
OVERALL	9.1882	9.3100	-1.2255
ABSOLUTE VALUE (Definition A)			
Men, Initial Age≤35	7.3997	7.6488	-2.5680**
Men, Initial Age>35	7.4887	7.7175	-1.9043**
OVERALL	7.4199	7.6869	-3.7569**
Women, Initial Age≤35	7.6180	7.9819	-3.2564**
Women, Initial Age>35	7.8779	8.0886	-1.2833*
OVERALL	7.6621	8.0259	-4.0706**
ABSOLUTE VALUE (Definition B)			
Men, Initial Age≤35	5.5723	5.7677	-2.0237**
Men, Initial Age>35	5.7705	6.0131	-1.9727**
OVERALL	5.6173	5.9039	-4.0052**
Women, Initial Age≤35	5.8627	6.2520	-3.2843**
Women, Initial Age>35	6.3162	6.4977	-1.0662
OVERALL	5.9396	6.3534	-4.3776**
DATA-BASED (Definition A)			
Men, Initial Age≤35	8.1962	8.2786	-0.8101
Men, Initial Age>35	8.4426	8.2622	1.3915*
OVERALL	8.2520	8.2695	-0.2315
Women, Initial Age≤35	8.3931	8.5609	-1.4947*
Women, Initial Age>35	8.6860	8.8005	-0.6646
OVERALL	8.4428	8.6597	-2.3890**

*Significant at 0.10 level; **Significant at 0.05 level.

A comparison of ‘typical’ successful biographies is then implemented in order to understand the importance of OMA and how this technique can help to extract non-evident information from sequence data. Table 7 shows for each group the sequences ending in permanent contract which present the lowest mean disagreement. That is, those sequences ending in ‘4’ with the lowest mean disagreement with respect to the rest of sequences ending in ‘4’ for each group. These sequences are addressed as ‘typical’ successful biographies. As can be observed, these sequences are almost identical for all groups: there are two or three initial non-employment states, followed in most cases by one or two temporary contracts; finally, a permanent contract is obtained at the fifth moment (the fourth one for men and women above 35, when the default or the data-based substitution cost matrix is used).

²⁴ This is relevant because the lack of significance of the t-statistic can be related to the relatively small sample size of the defined subgroups (the only exception if that of no-THA men above 35 years-old, who appear less dissimilar when the default and the data-based cost matrices are used).

Table 7. Typical sequences ending in permanent contract

	<u>Substitution cost matrix</u>		
	‘Default’	‘Absolute Value’*	‘Data-Based’
Men, Initial Age ≤35			
Sequence with lowest mean disagreement	11224444	11224444	11224444
Number of sequences	333	333	333
Mean dissimilarity	4.1994	3.3688	3.6715
Men, Initial Age >35			
Sequence with lowest mean disagreement	11244444	11124444	11244444
Number of sequences	204	204	204
Mean dissimilarity	4.3431	3.7647	3.8075
Women, Initial Age ≤35			
Sequence with lowest mean disagreement	11224444	11224444	11224444
Number of sequences	377	377	377
Mean dissimilarity	4.5620	3.6412	4.0398
Women, Initial Age >35			
Sequence with lowest mean disagreement	11244444	11224444	11144444
Number of sequences	101	101	101
Mean dissimilarity	4.4752	3.504	3.96

*Definition A

Those ‘typical’ successful biographies can be compared to the ‘typical’ general biographies (that is, wither successful or not). Those typical general biographies are obtained by comparing the sequences in each group to every other sequence in the group. Results are presented in Table 8. In general ‘typical’ general biographies are chaotic: in most cases their end is with a slighter attachment than previous states. Using the absolute value matrix, we appreciate that in the first part of the observed period the typical THA biography is quite similar to the typical biography ending in permanent contract. The differences are in the second half of the period, where a chaotic feature is detected in almost all cases. Nevertheless, the typical no-THA biographies present more changes between non-employment and temporary contracts (that is, they seem more chaotic, especially for women under thirty five years-old). Results are similar using the data based substitution cost matrix, although there are some differences between THA and no-THA subsamples for women.

Focusing on the results for women with or below 35, we can see the usefulness of OMA techniques. For this group the ‘typical’ general biography of the THA subsample seems not very distinct from the ‘typical’ general biography of the no-THA subsample. However, when we work out the mean dissimilarity of all sequences to every successful sequence, it is detected a robust difference between subsamples for this group.

To sum up, women with or below 35 who have experienced a job through a THA present labour market biographies —taken as wholes— which are more similar to successful labour market biographies. Depending on the substitution cost matrix, this similarity is between 2 to 6 per cent higher than for those who did not experience a job through a THA. For the remainder of groups, results are in the same way, although the differences in the mean dissimilarity between subsamples are not always statistically significant.

Table 8. Typical sequences

	THA Workers			No-THA Workers		
	<u>Substitution cost matrix</u>			<u>Substitution cost matrix</u>		
	Default	Absolute Value*	Data-Based	Default	Absolute Value*	Data-Based
Men, Initial Age ≤35						
Sequence with lowest mean disagreement	11122221	11122221	11122221	11122221	11122221	11122221
Number of sequences	1,098	1,098	1,098	432	432	432
Mean dissimilarity	6.5385	4.8024	5.8335	5.8703	4.1839	5.0980
Men, Initial Age >35						
Sequence with lowest mean disagreement	11112221	11122221	11112221	11112221	11122222	11122221
Number of sequences	322	322	322	539	539	539
Mean dissimilarity	7.3073	5.5089	6.6401	5.5905	5.8006	6.6032
Women, Initial Age ≤35						
Sequence with lowest mean disagreement	11122211	11222211	11122211	11121221	11121221	11121221
Number of sequences	1,136	1,136	1,136	359	359	359
Mean dissimilarity	7.0197	5.4178	6.3298	6,2343	4.6786	5.5232
Women, Initial Age >35						
Sequence with lowest mean disagreement	11112211	11122211	11112211	11111212	11111221	11111221
Number of sequences	232	232	232	252	252	252
Mean dissimilarity	7.0258	5.2715	6.2902	5.8492	4.0238	5.2413

*Definition A

5.2.3. Determinants of sequence dissimilarities: An application of the Blinder/Oaxaca methodology

In this section, we provide a more comprehensive treatment of differences across THA and no-THA workers. We seek to go beyond the descriptive results presented in the previous section, by assessing the role played (in access to ordered biographies) by labour experience through a THA. In addition, we take into consideration other factors in determining the likelihood that the individual enjoys a permanent contract at the end of the observation period. The model consists of variables to control both for initial conditions and other aspects which remain constant along time. We measure human capital of individuals (initial age and qualification group²⁵), the class and duration of the initial spell (non-employment, temporary or permanent status), the

²⁵ It must be underlined that the eleven professional categories of individuals contribution to the Social Security in the database do not collect workers' level of qualification, but the required level of qualification for the job. For instance, an individual working in the lowest category (*peón*) may well be in possession of an academic degree. In any case, we will refer to contribution categories from here onwards as "qualification", although this remark should be remembered for the subsequent analysis. We group those eleven categories in the following four: Qualification High collects the highest level in between the contribution categories, that is, 1 (*ingenieros* and *licenciados*), 2 (*ingenieros técnicos*, *peritos* and *ayudantes titulados*) and 3 (*jefes administrativos* and *de taller*); Qualification Medium-High collects contribution categories 4 (*ayudantes no titulados*), 5 (*oficiales administrativos*) and 6 (*subalternos*); Qualification Medium-Low collects contribution categories 7 (*auxiliares administrativos*) and 8 (*oficiales de primera* and *segunda*); finally, Qualification Low collect contribution categories 9 (*oficiales de tercera* and *especialistas*) and 10 (*peones*).

occupation sector, whether or not the employer is a public firm, and, finally, the region of the initial spell²⁶.

Our objective is to find the determinants of the dissimilarity index differential across both subsamples, and to distinguish in this process between individual characteristics and the impact of having been employed through a THA.

We estimated dissimilarity equations for THA and no-THA subsamples. The three different measures of substitution costs explained in Section 5.2.1 above are used to construct the mean dissimilarity that each individual in those two subsamples has with respect to the set of ordered sequences for the total sample. Those three measures of individual distances are taken as dependent variables in the estimations.

The separately estimated distance equations for THA and no-THA workers at the sample means is given by:

$$\bar{Y}_i = \hat{\beta}_{i,o} + \sum_{j=1}^N \bar{X}'^{(j)}_i \hat{\beta}_i^{(j)} \quad (9)$$

where i denotes THA or no-THA, the mean distance is given by $\bar{Y}_i$, the estimated intercept term is $\hat{\beta}_{i,o}$, $\hat{\beta}_i^{(j)}$ is a vector of estimated coefficients for the regressor comprising the j th variable, and $\bar{X}'^{(j)}_i$ is a vector of regressor means for the set of regressor comprising the j th variable.

The distance gap between THA and no-THA workers can be decomposed as follows into a portion “explained” by differences in characteristics as evaluated using THA individual’s coefficients, and a portion “unexplained”. This decomposition follows Blinder (1973) and Oaxaca (1973):

$$\bar{Y}_{THA} - \bar{Y}_{NO-THA} = (\hat{\beta}_{THA,o} - \hat{\beta}_{NO-THA,o}) + \sum_{j=1}^N \bar{X}'^{(j)}_{NO-THA} \Delta \hat{\beta}^{(j)} + \sum_{j=1}^N \Delta \bar{X}'^{(j)} \hat{\beta}_{THA}^{(j)} \quad (10)$$

where:

$$\Delta \hat{\beta}^{(j)} = \hat{\beta}_{THA}^{(j)} - \hat{\beta}_{NO-THA}^{(j)} \quad (11)$$

$$\Delta \bar{X}'^{(j)} = \bar{X}'^{(j)}_{THA} - \bar{X}'^{(j)}_{NO-THA} \quad (12)$$

²⁶ Appendix A reports the means and standard errors for the THA and no-THA subsamples. THA individuals are more likely to be women, younger and to be employed at jobs requiring slightly higher qualification levels at the beginning of the observation period. THA workers have a duration of their first observed spell (either of employment or unemployment) of 133 days; no-THA individuals experienced, by contrast, a duration of 155 days. Finally, both types of individuals are most likely to be non-employed at the beginning of the period, to be employed at the service sector and especially in Catalonia and Madrid (which account for almost half of employment spells).

The jth variable contributes to the unexplained portion of the distance gap —the second component of the right-hand-side of equation (10)— and to the explained portion of the distance gap —the last term of (10). The contribution of the intercept term to the unexplained component is given by the first component in the right-hand-side of equation (10).

Table 9: Ordinary Least Squares Estimates for THA and no-THA Dissimilarity Equations

	SUBSTITUTION COST MATRIX					
	Data-Based		Default		Absolute Value	
	THA	No-THA	THA	No-THA	THA	No-THA
Variable	$N=2,788$	$N=1,582$	$N=2,788$	$N=1,582$	$N=2,788$	$N=1,582$
Intercept	8.2958 ***	5.4942 ***	8.5433 ***	5.5987 ***	8.3296 ***	4.7963 ***
Sex	.1087 *	-.0829	.0998	-.1071	.0373	-.1130
Initial Age	-.1171 ***	.02877	-.1378 ***	.0415	-.1661 ***	.0310
Initial Age squared	.0020 ***	-.0001	.0023 ***	-.0003	.0027 ***	-.0001
Qualif.:						
High	-.9801 ***	-.6285 ***	-1.0801 ***	-.6636 ***	-.8901 ***	-.6510 ***
Med-High	-.4756 ***	-.3070 ***	-.5155 ***	-.3334 ***	-.4534 ***	-.3246 ***
Med-Low	-.2077 ***	-.2302 ***	-.2195 ***	-.2578 ***	-.2279 ***	-.2382 ***
Duration of initial spell	.0016 ***	.0022 ***	.00209 ***	.0025 ***	.0018 ***	.0023 ***
Class of initial spell:						
Temporary	2.2362 ***	2.1131 ***	2.9251 ***	2.6456 ***	1.4487 ***	1.2867 **
Non-employment	1.4169 ***	1.8004 ***	2.0806 ***	2.2090 ***	1.2182 ***	1.7909 ***
Occupation sector of initial spell:						
Service	.0763	.0690	.1463	.0012	.2457	.0992
Industry	-.4135	-.0698	-.4289	-.1424	-.2291	-.0882
Construction	.1185	.4040	.1800	.3677	.3844	.4103
Employer of initial spell:						
Public	.3653	.3960 ***	.4280 *	.4289 ***	.3947 *	.4479 ***
Region of initial spell:						
Andalucía	.3599 ***	.5130 ***	.4183 ***	.5544 ***	.4090 ***	.5237 ***
Aragón	.6291 ***	.3184	.6754 ***	.3133	.6497 ***	.2352
Asturias	.4292	.2096	.4829	.2080	.3492	.2506
Balears	.1987	-.0678	.2340	-.1159	.2844	.0011
Canarias	.1006	.3870 **	.1109	.3630 *	.1049	.4380 **
Cantabria	-.2880	.5722 *	-.2292	.6444 *	-.2459	.5400
Castilla-La-Mancha	-.7758	.3201	-.7841 *	.3244	-.6511	.3101
Castilla-León	.4773 ***	.5869 ***	.5329 ***	.6151 ***	.5912 ***	.5692 ***
Catalonia	-.1045	-.1527	-.1144	-.1517	-.0916	-.1668
Valencia	.0508	.3178	.0671	.2909 *	.1388	.3612
Extremadura	-.0464	-.0347	-.0614	-.0531	.1561	-.0218 **
Galicia	.4337 ***	.0576	.4338 ***	.0133	.3189 **	.0547
Murcia	.2014	.0688	.2035	.0343	.3032	.1879
Navarra	.0780	-.7539	.0252	-.8615	.1280	-.7234
País Vasco	.1064	.2417	.1008	.2414	.0739	.2302
La Rioja	-.9326 ***	.7447	-1.0700 ***	.7301	-.7960 **	.6881
Ceuta and Melilla	.8119	.3882	.8441	.2363	.3461	.5740
R ²	0.1582	0.2054	0.1742	0.2174	0.1653	0.2096
F-value	17.28 ***	13.36 ***	19.39 ***	14.36 ***	18.20 ***	13.71 ***

Notes: The dependent variable is the average dissimilarity of each individual in the subsample to the sequences that end in permanent contracts for the total sample. Reference individual: Qualification Low, Permanent initial spell, Agriculture sector, Private employer, Madrid.

* = Significant at 0.10 level

** = Significant at 0.05 level

*** = Significant at 0.01 level or better

Coefficient estimates for equations (9) are given in Table 9. Estimated average distances to ordered sequences by THA and no-THA individuals differ according to the type of distance measure used. However, both the duration of the initial spell observed and the observation of a non-permanent type of contract are significant contributors to higher distances in both subsamples. In addition, the average individual distance is reduced by age and qualification required for the job. Individuals employed in a public firm show a larger distance than those in the reference group (private employer), as well as those initially employed in Andalucía, Aragón, Castilla-La-Mancha and Extremadura (when compared to those in Madrid).

The decomposition detailed in Equation (10) is showed in Table 10. When the default distance measure is used as dependent variable, around half of the gap can be accounted for by differences in independent variables. However, when the data-based or the absolute value measures are used, differences in characteristics now only explain a percentage well below 50 percent of the gap. With the data-based distance measure, differences in human capital and job-related characteristics of individuals account for 38.66 percent of the gap. Qualification and the class and duration of the spell explain a sizeable percentage of the gap. With the absolute value distance measure, characteristics only account for 22.09 percent. In this case, age, the region and duration of the initial spell, and qualification are the most important variables.

The most relevant result is that —compared to being in a non-employment state— having worked through a THA is by far the chief factor explaining individuals' distance to the sequences ending in permanent contracts. Although the regressions obviously omit some productivity-related characteristics (such as, for instance, education and its quality, or work experience), the unexplained distance gap between THA and no-THA individuals is so large that it seems unlikely to be due to omitted variables. In any case, the THA and no-THA omitted characteristics would have to be very large to account for the unexplained portion of the THA-no THA distance gap²⁷.

Therefore, either because individuals who have worked through a THA are somehow different from the rest —and this agency experience is a signal of those variables which are making them different— or because the THA adds “value” to the individual (in order to achieve a permanent contract in the future), those high unexplained portions of the distance gap across subsamples indicate that the labour market values having worked through a THA in the sense that the comparative easiness in the attainment of an ordered biography is substantially larger compared to our no-THA subsample.

Table 10: Determinants of THA–no THA Dissimilarity Differentials

	SUBSTITUTION COST MATRIX					
	Data-Based		Absolute Value		Default	
<i>Description</i>	Absolute gap	Percentage gap	Absolute gap	Percentage gap	Absolute gap	Percentage gap
Gap	-.1586	100 %	-.3226	100 %	-.1383	100 %
Unexplained Gap	-.0973	61.3 %	-.2513	77.9 %	-.0657	47.5 %
Explained Gap	-.0613	38.6 %	-.0713	22.0 %	-.0725	52.4 %
<i>Explained by:</i>						
Sex	-.0114	7.1 %	-.0039	1.2 %	-.0104	7.5 %
Age*	.0239	-15.0 %	.0699	-21.6 %	.0317	-22.9 %
Qualification*	-.0405	25.5 %	-.0384	11.8 %	-.0441	31.9 %
Class of spell*	.0363	-22.8 %	.0100	-3.1 %	.0373	-26.9 %
Duration of spell	-.0362	22.8 %	-.0404	12.5 %	-.0447	32.3 %
Occupation Sector*	.0228	-14.3 %	.0079	-2.4 %	.0295	-21.3 %
Public employer	-.0294	18.5 %	-.0317	9.8 %	-.0344	24.8 %
Region*	-.0270	16.9 %	-.0448	13.8 %	-.0373	26.9 %

Note: This table is based on regression results for THA and no-THA subsamples showed in Table 9. * = Algebraic sum of the contribution of those explanatory variables to the explained gap (for the vector of qualification, class, occupation and region dummies, and for the variable age).

²⁷ Due to the limits of the applied methodology, this result indicates an upper limit of the influence of obtaining a job through a THA compared to a non-employment situation.

6. Conclusion

Our main objective in this paper is to find out to what extent workers hired temporarily by a THA may enjoy better prospects of moving out of temporary job positions and reaching permanent contracts than those who have, in contrast, no position with those intermediaries in their work history. For this purpose, we have proposed the use of a relatively new empirical methodology to analyse the influence of THA intermediation over the dynamics of individuals' attachment to the labour market. This method —previously applied in Sociology— consists of analysing sequences of events taken as wholes, whilst the usual method consists of estimating the determinants of transitions across labour market states. Few studies so far have attempted to examine the full long-term *trajectory* or *sequence* of individuals' labour market attachment.

This “unfolding” over time cannot be expressed in terms of a single transition: only a temporarily ordered sequence of events captures the essence of the life-course insights. Therefore, it becomes crucial to examine sequences of jobs over time in order to understand individuals' career trajectories (i.e., labour market biographies). Our focus facilitates a comprehensive understanding of mobility patterns in the labour market. We argue that these techniques allow us to (1) identify empirically common career trajectories; and (2) examine how individuals' mobility patterns and attachments to different labour market status unfold and evolve over the life course.

The conceptual framework proposed by Spilerman (1977) has been widened in order to define the labour market biography as the sequence of labour market states along time. Two subsamples of workers —one of them constituted by individuals experiencing a job through a THA and the other by non-employed individuals—are comparatively analyzed. The analysis of modes and medians of sequences has shown differences by gender, but not by age inside each subsample. In addition, the sequences for men and women are closer in the THA subsample than in the no-THA subsample. The application of OMA techniques has proved that a relationship between THA intermediation and successful labour market biographies is detected for women with or below 35. The rest of groups presents similar results but with a lower robustness.

In addition, we have found evidence that the main reason for the gap between THA and no-THA workers' distances to ordered sequences was precisely due to the fact of having been employed through one of those intermediaries. The Blinder/Oaxaca decomposition of the distance gap across subsamples reveals that differences in measured characteristics may explain only under one-third of the gap. Conclusions must be tempered by the acknowledgment that —because agency workers are compared with unemployed (but not with those employed at the same moment without the intermediation of a THA)— the data extraction process avoids a proper evaluation of the role played by THAs. But even in spite of this, results support the view that, when comparing THA individuals to non-employed, having been a THA workers is the chief factor explaining progress towards a permanent contract status. Thus, the paper questions some widespread belief on the presumed detrimental effects of THAs on workers' employment prospects.

Apart from a comparative evaluation of THA and no-THA individuals, our longitudinal methodological approach has constituted a powerful tool for the study of labour market trajectories. This procedure allows us to better understand the temporary nature of labour market attachment patterns. We hope that it will also offer new insights in subsequent economic analyses of life course sequential processes over time.

APPENDIX A: Mean Characteristics of THA and no-THA subsamples

Variable	THA N= 2,788	No-THA N= 1,582
Sex	.5093 (.5000)	.6137 (.4870)
Initial Age	27 (7.1022)	30 (6.0563)
Initial qualification group:		
High	.0828 (.2757)	.0594 (.2364)
Medium-High	.1646 (.3709)	.1396 (.3467)
Medium-Low	.3748 (.4841)	.3476 (.4763)
Low	.3776 (.4848)	.4532 (.4979)
Duration of initial spell (in days)	133 (281.718)	155 (289.6962)
Class of initial spell:		
Non-employment	.9246 (.2639)	.9696 (.1715)
Temporary	.0706 (.2563)	.0259 (.1589)
Permanent	.0046 (.0681)	.0044 (.0663)
Occupation sector of initial spell:		
Service	.8579 (.3491)	.6422 (.4794)
Industry	.1090 (.3117)	.1681 (.3741)
Construction	.0301 (.1709)	.1826 (.3865)
Agriculture	.0028 (.0534)	.0069 (.0831)
Employer of initial spell:		
Public	.0175 (.1314)	.0979 (.2973)
Region of initial spell:		
Andalucía	.0857 (.2800)	.1833 (.3870)
Aragón	.0200 (.1403)	.0183 (.1341)
Asturias	.0096 (.0979)	.0227 (.1491)
Balears	.0086 (.0923)	.0189 (.1364)
Canarias	.0222 (.1474)	.0499 (.2178)
Cantabria	.0050 (.0706)	.0139 (.1171)
Castilla-La-Mancha	.0060 (.0778)	.0372 (.1895)
Castilla-León	.0337 (.1805)	.0398 (.1956)
Catalonia	.2894 (.4535)	.2060 (.4046)
Valencia	.0703 (.2557)	.1169 (.3214)
Extremadura	.0086 (.0923)	.0233 (.1511)
Galicia	.0509 (.2198)	.0524 (.2230)
Madrid	.2604 (.4389)	.1649 (.3712)
Murcia	.0154 (.1232)	.0164 (.1271)
Navarra	.0157 (.1246)	.0063 (.0792)
País Vasco	.0868 (.2815)	.0259 (.1589)
La Rioja	.0075 (.0864)	.0025 (.0502)
Ceuta and Melilla	.0035 (.0597)	.0006 (.0251)

Notes: Standard errors in parentheses.

APPENDIX B: Basic Optimal Matching Algorithm

If the elementary operations consist only of insertions, deletions and substitutions, the distance measure can be calculated with a simple dynamic programming method. To explain this method, we mainly follow Kruskal and Sankoff (1983, pp. 266).²⁸

Let $\mathbf{Y}$ denote the finite state space and ϕ an “empty state” which is not contained in $\mathbf{Y}$. The cost functions are:

$$\psi(x, y) = \text{substitution cost, } x, y \in \mathbf{Y}$$

$$\psi(x, \phi) = \text{deletion cost, } x \in \mathbf{Y}$$

$$\psi(\phi, y) = \text{insertion cost, } y \in \mathbf{Y}$$

The expression:

$$\begin{bmatrix} x_1 & \dots & x_p \\ y_1 & \dots & y_p \end{bmatrix} \quad (1)$$

²⁸ Computations for this algorithm have been implemented through the use of the computer program called TDA (*Transition Data Analysis*), which is publicly available at the following web site: <http://steinhaus.stat.ruhr-uni-bochum.de/tda.html>

is called an *alignment* if $x_i, y_i \in \mathbf{Y} \cup \{\phi\}$ and there is no column with $x_i = y_i = \phi$. The *length* of an alignment (i.e., the distance between the two sequences) is defined by $\sum_i w(x_i, y_i)$.

Now, let $a=(a_1, \dots, a_m)$ and $b=(b_1, \dots, b_n)$ be two sequences with states in $\mathbf{Y}$. We say that (1) is an alignment between the sequences a and b if by inserting empty states into a it can be made equal to $x=(x_1, \dots, x_p)$, and in the same way b can be made equal to $y=(y_1, \dots, y_p)$. Given this definition, we can finally define the (standard) distance between a and b , denoted $d(a, b)$, as the minimum possible length of any alignment of these two sequences. Additional notation to describe the algorithm is: $a^i=(a_1, \dots, a_i)$, $b^j=(b_1, \dots, b_j)$, and $d_{ij}=d(a^i, b^j)$.

Using this notation, we need to calculate $d(a, b)=d_{mn}$. This can be done by calculating the elements of the $(m+1, n+1)$ matrix $D=(d_{ij})$ ($i=0, \dots, m$; $j=0, \dots, n$) recursively in the following way. The first step is initializing the first row and first column of this matrix:

$$\begin{aligned} d_{0,0} &= 0 \\ d_{0,j} &= d_{0,j-1} + w(\phi, b_j) \quad j=1, \dots, n \\ d_{i,0} &= d_{i-1,0} + w(a_i, \phi) \quad i=1, \dots, m \end{aligned}$$

All other elements of D can then be calculated by using three predecessors. The recurrence relation is:

$$d_{ij} = \min \{d_{i-1,j} + w(a_i, \phi), d_{i-1,j-1} + w(a_i, b_j), d_{i,j-1} + w(\phi, b_j)\}$$

Having calculated all elements of D , one finally finds the required distance in the element d_{mn} .

REFERENCES

- Abbot, A. (1983) Sequences of Social Events. *Historical Methods*, 16: 129–147.
- _____ (1990) A Primer on Sequence Methods. *Organization Science*, 1:373–392.
- _____ (1991) The Order of Professionalization. *Work and Occupations*, 18(4):355–384.
- _____ and Hrycak, A. (1990) Measuring Resemblance in Sequence Data: An Optimal Matching Analysis of Musicians' Careers. *American Journal of Sociology*, 96(1): 144–185.
- Abraham, K.G. (1990) Restructuring the Employment Relationship: The Growth of Market Mediated Work Arrangements. In: Abraham, K. and R. McKersie (eds) *New Developments in the Labour Market: Toward a New Institutional Paradigm*. Massachusetts Institute of Technology. Cambridge, Mass.: 85–119.
- Abraham, K.G. and S. Taylor (1996) Firm's use of Outside Contractors: Theory and Evidence. *Journal of Labour Economics*, 14 (3):394–424.
- Belous, R. S. (1989) How Human Resource Systems Adjust to the Shift Towards Contingent Workers, *Monthly Labour Review*, 109, 7–12.
- Berger, P.A., Steinmuller, P. and Ziegler, Z. (1993) Upward Mobility in Organisations: The Effects of Hierarchy and Opportunity Structure. *European Sociological Review*, 9:173–188.
- Blank, R.M. (1998) Contingent Work in a Changing Labour Market. In Richard B. Freeman and Peter Gottschalk (eds.). *Generating Jobs. How to Increase Demand for Less-Skilled Workers*. New York, Russell Sage Foundation: 258–294.
- Blinder, A.S. (1973) Wage Discrimination: Reduced Form and Structural Elements. *Journal of Human Resources*, vol. 8, no. 4 (Fall): 436–455.
- Bronstein, A.S. (1991) Temporary Work in Western Europe Threat or Compliment to Permanent Employment? . *International Labour Review*, December: 29–35.
- Carey, M. L. and K.L. Hazelbaker (1986) Employment Growth in the Temporary Help Industry. *Monthly Labour Review*, April:37–44.
- Chan, J.W. (1994) Tracing Typical Mobility Paths. Ms. Nuffield Coll. Oxford.

- Emerson, M. (1988) Regulation or Deregulation of the Labour Market . *European Economic Review*, 32: 775–817.
- Forbes, A. F. (1971) Markov Chain Models for Manpower Systems. In: D.J. Bartholomew and A.R. Smith (eds.), *Manpower and Management Science*, London: Heath: 93–113
- Forrest, J., and A. Abbot (1990) The Optimal Matching Method for Anthropological Data . *Journal of Quantitative Anthropology*, 12:151–170.
- Gillespie, Jackson F., W. E. Leininger, and H. Kahalas (1976) A Human Resource Planning and Valuation Model , *Academy of Management Journal*, 19: 650–656.
- Halpin, B. and T. W. Chan (1998) Class Careers as Sequences: an Optimal Matching Analysis of Work-Life Histories , *European Sociological Review*, 14: 113-130.
- Hogan, D.P. (1978) The Variable Order of Events in the Life Course , *American Sociological Review*, 43: 573–586.
- Kruskal and Sankoff (1983) An Anthology of Algorithms and Concepts for Sequence Comparisons . In: D. Sankoff, J.B. Kruskal (eds.), *Time Warps, String Edits, and Macromolecules: The Theory and Practice of Sequence Comparisons*, Reading: Addison–Wesley: 265–310
- Mahoney, T.A. and G.T. Milkovich (1971) The Internal Labour Market as a Stochastic Process , in D.J. Bartholomew and A.R. Smith (eds.), *Manpower and Management Science*, London: Heath: 75–91
- Mangum, G., D. Mayall and K. Nelson (1985) The Temporary Help Industry: Response to the Dual Labour Market . *Industrial and Labour Relations Review*, 28: 599–611.
- Moberly, R. M. (1987) Temporary, Part–Time and Other Atypical Employment Relationships in the United States. *Labour Law Journal*, November: 689–696.
- Muñoz–Bullón, F. (1999) Análisis Económico y Empresas de Trabajo Temporal, *Documentación Laboral*, no. 60 (III): 39–75.
- National Association of Temporary and Staffing Services (1994) 1994 Profile of the Temporary Workforce. *Contemporary Times*, a Publication of the National Association of Temporary and Staffing Services, Alexandria, Va, Spring.
- Oaxaca, R. L. (1973) Male-Female Differentials in Urban Labor Markets . *International Economic Review*, vol. 14, no. 3 (October): 693–709.
- Piore, M. (1975) Notes for a Theory of Labor Market Stratification , chapter in R.C. Edwards, M. Reich and D.M. Gordon (eds.), *Labor Market Segmentation*, Lexington, Mass.: Lexington Books: 125–149.
- Polivka, A.E. and T. Nardone (1989) On the Definition of ‘Contingent Work’ , *Monthly Labour Review*, 109: 3–9.
- Rodríguez–Piñero Royo, M.C. (1992) *Cesión de Trabajadores y Empresas de Trabajo Temporal*. Ministerio de Trabajo y Seguridad Social, Madrid.
- _____ (1994) *Las Empresas de Trabajo Temporal en España*. Tirant lo Blanch, Valencia.
- Segal, L. (1996) Flexible Employment: Composition and Trends’’. *Journal of Labour Research*, vol. XVII, no. 4: 525–542.
- Segal, L. and D.G. Sullivan (1997) The Growth of Temporary Services Work . *Journal of Economic Perspectives*, 11 (2): 117–136.
- Spilerman, S. (1977) Careers, Labour Market Structure and Socioeconomic Achievement , *American Journal of Sociology*, vol. 83, nº 3: 551–593.
- Vroom, V.H. and K. R. MacCrimmon (1968) Toward a Stochastic Model of Managerial Careers , *Administrative Science Quarterly*, vol. 13: 26–46.
- Wilensky, H. (1961) Orderly Careers and Social Participation: The Impact of Work History on Social Integration in the Middle Mass , *American Sociological Review*, 26 (August): 521-539.