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in the Spanish Labour Market**

por

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Job Match Quality throughout the Business Cycle in the Spanish Labour Market

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Abstract

Recent empirical evidence for the US economy suggests that job matches created during economic expansions turn out to be of better quality than job matches created during economic recessions. We discuss different measures of job mismatching for the Spanish labour market: (i) measures based on the degree of adjustment between job requirements and workers' qualifications; and (ii) measures based on the duration of the job match (Jovanovic, 1979). Given our data limitations and the duality of the Spanish labour market we follow the second approach and define a good job match as a temporary contract that is converted into a permanent one. We find, as expected, that temporary matches created during periods of economic recession are less likely to be converted into permanent contracts than temporary matches created in periods of economic expansion. However, contrary to other available empirical findings for the US, this cyclical pattern of job match quality in the Spanish labour market appears to be due to a "stop-gap" job phenomenon: during recessions unemployed Spanish workers are more willing to accept jobs that require lower skills while they await better opportunities when the business cycle recovers.

JEL codes: J24, J41.

Keywords: job match quality, business cycle, Spanish labour market.

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1 Introduction

Matching is a lengthy and costly process. It is not an easy task to find your “better half”. Likewise it is not easy in the labour market. Filling a job vacancy with the right employee requires time and resources. On the one hand firms open vacancies and advertise them in newspapers, on the internet, etc. They even procure candidates through casual conversations with friends. After this they interview the potential candidates and select the one they think qualifies best for the job. On the other hand, unemployed workers search for vacancies, send in their CVs and pass exams, interviews and even psychological tests. This is such a thorough process that in many cases firms and unemployed workers require the help of employment agencies.

Therefore the matching process becomes a key issue for the firm, especially in those countries where legal restrictions make it very expensive to dissolve the match. Furthermore, whether or not firms and unemployed workers match each other successfully has clear and direct effects on aggregate variables such as unemployment rates, productivity, job creation, job destruction, wages, etc.

The labour literature has studied the matching process in detail, and there have been many empirical contributions that try to identify the features that facilitate job matches¹. An important part of this research has consisted in isolating the roles that unemployment benefits and unemployment duration play in job matching². Many studies have also been devoted to identifying the features that affect job match quality³.

In this paper we study the role that the business cycle plays in determining the quality of job matches in the Spanish labour market. The status of the business cycle when the match is first created will affect job match quality insofar as it influences the outside option of the match participants. During recessions employers are able to meet more and better candidates since the pool of unemployed workers is larger. Hence, the quality of job matches created during recessions may be higher (agglomeration effect). However, at the same time, as the pool of unemployed workers increases, the outside option of candidates gets worse, leading them to accept the first offer they receive. This may lead to worse job matches during recessions (congestion effect). Therefore the overall effect of the business cycle on job match quality predicted by the theory seems ambiguous. However the empirical evidence suggests that the congestion effect outweighs the agglomeration effect.

¹See Petrongolo and Pissarides (2001) for a recent survey on the “search and matching” literature.

²Lancaster (1979), Nickell (1979), Narendranathan et al. (1985), Pissarides (1999) and Bover et. al (2002). Devine and Kiefer (1991) is also a good survey on the empirical studies.

³Burdett (1979), Akerloff et al. (1988), Marimon and Zilibotti (1999), Bowlus (1995), Centeno (2002) and Addison (2000), Arranz and García-Serrano (2003).

Using the NLSY⁴ and defining tenure in the job as a proxy for match quality (Jovanovic, 1979), Bowlus (1995)⁵ and Centeno (2002)⁶ obtain that job matches created during expansions last longer and therefore turn out to be of better quality than job matches created during recessions. Moreover Bowlus (1995) argues that this cyclical phenomenon is one of general mismatching rather than an increase in the number of “stop-gap” jobs⁷ during economic downturns. Centeno (2002) also obtains that the eroding effect of the cycle during economic downturns appears to be mitigated by the generosity of the State unemployment insurance system.

Regarding the evidence for the Spanish labour market several studies have analysed the determinants of the duration of job matches. However none of them measures the role of the status of the business cycle when the match is first created.

García-Fontes and Hopenhayn (1996) and García-Pérez (1997) analyse job matches created during the period 1978-1992 using data from the Social Security Register. The main drawback of this dataset is that it does not allow us to distinguish between job matches created under temporary or permanent contracts. Both studies differ on the specification of the hazard rate⁸ and focus primarily on the role that the current state of the business cycle plays in job match ending.

García-Fontes and Hopenhayn (1996) use a set of quarterly dummies that take value one whenever the job match ends. They find that voluntary match-ends are procyclical while lay-offs seem to be moderately countercyclical. Moreover, they argue that lay-offs significantly increased after 1984. García-Pérez (1997) obtains similar results using the quarterly national GDP growth rate to control for the current state of the business cycle throughout the duration of the job match. When he controls for matches created after 1984 the probability of a job match ending because of a lay-off is countercyclical.

Using a different dataset, the ECBC⁹, García Serrano and Malo (1997) use a duration model to test whether education mismatching affects the probability of the job match ending. In this case the dataset allows them to distinguish between job matches created under a permanent or a temporary contract. However, despite using a sample of job matches created and destroyed at different time periods, they do not introduce any control for the business cycle.

⁴National Longitudinal Survey of Youth

⁵Bowlus (1995) uses a sample of 2135 job matches created during the period 1977-1988.

⁶Centeno (2002) uses a sample of 2688 job matches over the period 1979-1998.

⁷The term “stop-gap” jobs refers to matches that ex-ante are not expected to last when the economy starts to recover from recession.

⁸While García-Fontes and Hopenhayn (1996) use a proportional hazard model (Cox, 1972), García-Pérez (1997) uses a more flexible specification where the duration dependence is estimated using a polynomial on $\log(t)$.

⁹Encuesta de Conciencia y Biografía de Clases, 1991

More recently, Arranz and García-Serrano (2003) have also studied the influence of previous job experiences and unemployment experiences on job match duration. Using a random sample extracted from the HSIPRE¹⁰ for the period 1987-1997, they find evidence corroborating the countercyclicality of job match ending because of a lay-off. However, as in the previous studies, they do not introduce any control for the status of the cycle when the match is first created.

A review of the literature leads us to conclude that there has not been a thorough analysis of the role that the status of the business cycle, when the contract is first created, plays in determining the duration of job matches and thus in determining the quality of job matches in the Spanish labour market.

In the following section we will review the different measures of job match quality. We distinguish between two approaches: job match quality measured by the degree of adjustment between job requirements and workers' qualifications; and job match quality proxied by job match duration. We discuss the advantages and disadvantages of each approach in measuring the role of the business cycle, when the match is first created, in determining the quality of job matches. Following Güell and Petrongolo (2003) we discuss an alternative proxy to measure job match quality in the context of the Spanish labour market: the probability of converting a temporary contract into a permanent one. In sections 3 and 4 we present the data and the econometric model we will use. Our interest focuses on identifying the effect that the status of the business cycle, when the temporary match is first created, has on the probability of converting that match into a permanent contract within the firm. Thus, it is of prime importance to distinguish between the effect of the business cycle at the beginning of the match, the effect of the current status of the business cycle and the effects of the different regulatory benchmarks.

In section 5 we discuss the results. As in Bowlus (1995) we obtain that the Spanish labour market is characterized by a higher amount of job mismatching during recessions than during expansions. However, contrary to what Bowlus (1995) reports for the US economy, there does not seem to be a problem of general mismatching. When we analyse the effect of the current business cycle and the effect of the status of the cycle, when the match is first created, across different occupational groups, we obtain that the status of the business cycle, when the match is first created, only affects "stop-gap" jobs. That is, it only affects those occupations that do not need high qualification requirements and that are accepted by unemployed workers while waiting for the cycle to recover. Finally, section 6 concludes.

¹⁰Historical Benefit Integrated System.

2 Measuring job match quality

Job match quality has traditionally been measured in two different ways. Firstly, it can be measured by the degree of adjustment between job requirements and workers' qualifications. This is the approach followed in studying issues of occupational mobility (Sicherman and Galor, 1990 and Alba, 1991) and issues of overeducation (Verdugo and Verdugo, 1989; García-Montalvo, 1995; Kiker et al., 1997; Madrigal, 2003; and Oliver et al., 2003). In fact there is a growing literature that has focused primarily on identifying the causes and quantifying the features affecting overqualification. However, as far as we know, this approach has not been used in identifying the role that the status of the business cycle, at the point of match creation, plays in job mismatching¹¹.

The second approach to measuring job match quality has its origin in the definition of job matches as “experienced goods” (Jovanovic, 1979). In the context of asymmetric information between employers and employees, the productivity of the match only becomes apparent as the match evolves. Hence matches must be experienced in order to check their quality. Using this approach, job match quality can be proxied by the duration of the match: good matches endure while bad matches break up. This is the approach followed in Bowlus (1995) and Centeno (2002) for the US economy and in García-Fontes and Hopenhayn (1996) and García-Pérez (1997) for the Spanish labour market.

The literature distinguishes three types of measures of job mismatching based on the degree of adjustment between job requirements and workers' qualifications: subjective, objective and statistical measures¹². The subjective measures quantify the level of mismatching by comparing the level of education attained by each worker with the worker's opinion regarding the qualification required to perform the job properly (García-Serrano and Malo, 1997, Alba, 1991, and Sicherman and Galor, 1990). The objective measures quantify the level of mismatching by comparing the level of education attained by each worker with an independent and fixed scale of requirements for each occupation (Rumberger, 1997 and García-Montalvo, 1995, Kiker et al., 1997, and García-Montalvo et al, 2003). Finally, the statistical measures quantify the level of mismatching by comparing the level of education attained by each worker with the *mean* or the *mode* of the years of education within each occupational category (Verdugo and Verdugo, 1989, Kiker et

¹¹Oliver et al. (2003) present the evolution of the percentage of overeducated workers for the period 1980-2001 (p.30). They argue that overeducation seems to decrease during recessions, especially during the 92-94 economic downturn. The reason is the large amount of job destruction among the 16-30 age group, the one that presents the highest level of education attainment.

¹²See Madrigal (2003) and Oliver et al. (2003) for an extense review of the different measures.

al., 1997, and Oliver et al., 2003).

In Table 2.1 we present a comparison of the levels of educational-job mismatching obtained in the literature for the Spanish labour market. We observe that results vary a lot from one measure of overeducation to another (in 1991, the percentage of overeducation ranges between 6.59% and 28.4%), and that the subjective measures are always the ones that give a higher rate of overeducated workers. Regarding the cycle, the time pattern is not clear either, since it depends on the statistic we use to measure it. Using the *mode* Oliver et al. (2003) obtain an increasing time pattern, while using a broader interval, *mode plus/minus 40%*, they obtain a procyclical pattern for the percentage of overeducated workers.

MEASURES OF JOB MISMATCHING BASED ON THE DEGREE OF ADJUSTMENT BETWEEN JOB REQUIREMENTS AND WORKER S QUALIFICATIONS						
OBJECTIVE MEASURE						
Author	Year	Survey		Overeducation	Undereducation	Adequate
García-Montalvo (1995)	1985	EPA		3.68	30.45	65.87
García-Montalvo (1995)	1987	EPA		5.09	31.24	63.67
García-Montalvo (1995)	1989	EPA		6.34	62.57	31.09
García-Montalvo (1995)	1991	EPA		6.59	30.49	62.92
Beneito et al. (1996)	1991	ECBC		25.6	16.5	57.9
García-Montalvo (1995)	1993	EPA		7.7	27.61	64.69
STATISTICAL MEASURE						
Author	Year	Survey	Measure	Overeducation	Undereducation	Adequate
Oliver et al. (2003)	1980	EPA	mode	16.3	-	-
Oliver et al. (2003)	1987	EPA	mode	27.4	-	-
Oliver et al. (2003)	1993	EPA	mode	33	-	-
Oliver et al. (2003)	2000	EPA	mode	33.5	-	-
Oliver et al. (2003)	1980	EPA	mode +/- 40%	11.5	-	-
Oliver et al. (2003)	1987	EPA	mode +/- 40%	17.8	-	-
Oliver et al. (2003)	1993	EPA	mode +/- 40%	15.1	-	-
Oliver et al. (2003)	2000	EPA	mode +/- 40%	15.6	-	-
García-Montalvo (1995)	1993	EPA	mean +/- std	8.94	6.21	84.86
Beneito et al. (1996)	1991	ECBC	mean	15.2	15.3	69.5
SUBJECTIVE MEASURE						
Author	Year	Survey		Overeducation	Undereducation	Adequate
Alba (1993)	1985	ECTV		17.13	23.13	59.73
García-Serrano and Malo (1996)	1991	ECBC		28.4	30	41.7
García-Serrano and Malo (1996)	1991	ECBC		29.4	11	59.6
Beneito et al. (1996)	1991	ECBC		27.9	10.9	61.2

Source: Oliver et al. (2003)

Table 2.1. Measures of job mismatching in the literature.

In this study we are interested in measuring the role that the status of the business cycle, at the point of job match creation, plays in determining job match quality. The available time series data for the Spanish economy (EPA¹³) does not allow us to use either an objective or a subjective measure of job mismatching. In fact, we only have access to time series data of what has been defined as statistical measures of overeducation.

In Table 2.2 we report the evolution of the percentage of overeducated (also adequately educated) newly hired workers in Spain over the period 1987-2001¹⁴. We construct four different statistical measures. The first two are constructed using the *mean* while the last two are constructed using the *mode*. Each of the first two, as well as each of the last two measures, differs on the ranges used to consider a worker as adequately matched to a job. In the case of *mean* and *mode* with *constant interval* we have defined one single range of mismatching according to the occupational distribution of the years of education in 1987. In the case of *mean* and *mode* with *yearly intervals* we have defined fifteen ranges of mismatching, one for each year, according to the occupational distribution of the years of education in each year.

Percentage of overeducated/adequately-educated workers among the new hirings by year								
	Mean (constant interval)		Mean (yearly interval)		Mode (constant interval)		Mode (yearly interval)	
	Over-educated	Right-educated	Over-educated	Right-educated	Over-educated	Right-educated	Over-educated	Right-educated
1987	14.95	81.77	14.95	81.77	36.44	57.41	36.44	57.41
1988	16.02	80.87	16.02	80.87	39.13	54.14	37.25	54.02
1989	18.36	78.83	17.25	79.94	43.14	50.19	41.48	50.41
1990	17.55	79.45	16.43	80.55	44.48	47.65	42.75	48.06
1991	17.45	79.39	16.18	80.62	44.53	46.87	42.51	47.25
1992	18.29	78.33	17.19	79.36	46.77	45.35	44.84	45.83
1993	19.42	77.18	16.89	79.67	48.93	42.54	46.54	43.03
1994	19.46	78.16	16.57	76.95	49.33	43.1	41.32	46.09
1995	21.37	76.02	17.87	75.28	51.77	40	43.47	43.3
1996	22.7	74.49	19.73	73.78	54.47	36.98	46.44	40.51
1997	24.81	73.01	22.02	72.31	55.65	36.71	48.27	40.53
1998	26.73	71.17	23.5	69.57	58.65	33.75	51.16	37.56
1999	27.47	70.38	21.27	70.88	59.26	32.69	49.62	37.9
2000	28.72	68.64	22.02	64.58	58.52	32.35	48.76	37.12
2001	29.19	68.1	21.91	66.02	59.73	30.7	44.1	38.18

Table 2.2. Percentage of overeducated/ adequately educated workers among the new hirings by year.

¹³Encuesta de Población Activa or Spanish Labour Force Survey.

¹⁴We report data for the second quarter of each year. A *newly hired worker* is defined as a worker who is observed as employed in the second quarter of a given year while declaring to have not been working in the second quarter of the previous year. *Overeducation* has been measured as the percentage of newly hired workers who are over the average plus one standard deviation of the years of education of all workers within the same occupation. The occupational classification has been constructed following Oliver et al. (2003): pp.116-118.

As we can observe the Spanish pattern of overeducation has been increasing independently of the status of the business cycle. The reason may be twofold: (i) the increasing level of education of the cohorts entering the labour market¹⁵; and (ii) the increasing participation of the more highly educated, female population.

However, the size of the increase in the pattern of overeducation varies depending on the measure we use. On the one hand, working with moving ranges (one for each year) may underestimate the change in job mismatching, especially in a labour market that has experienced a boom of highly educated entrants. On the other hand, working with a fixed range (the same for each year) implies assuming that the educational requirements within each occupational group have remained constant for the whole period. This last measure, however, may overestimate the change in job mismatching.

Moreover, when we control for the characteristics of the individuals (see Table 2.3 and Table 2.4) the role that the status of the business cycle, at the point of match creation, plays in determining the probability of mismatching seems to depend crucially on the measure of job mismatching we choose. Results show that when we use the *mode* with *constant* or with *moving intervals* (see Tables A.1 and A.2 in the appendix) or the *mean* with *constant intervals* (see Table 2.3), job matches created during recessions are less likely to be correctly matched in as far as qualifications are concerned. However, when we use the *mean* with *moving intervals* (see Table 2.4), the opposite result is obtained.

¹⁵The data shows that the average years of studies of the working population between 20 and 64 years old in 1987 was 7.18 compared to a 9.46 in 2001.

Multinomial Logit for adequacy between education and occupation				
Mean (constant interval)				
	OVEREDUCATION		UNDEREDUCATION	
	coefficient	exp(B)	coefficient	exp(B)
Male	0.440 (0.000)	1.552	-0.193 (0.000)	0.824
Age 31-40	-0.318 (0.000)	0.728	-0.064 (0.263)	0.938
Age 41-50	-0.701 (0.000)	0.496	0.045 (0.502)	1.046
Age51-64	-1.225 (0.000)	0.294	0.069 (0.372)	1.072
Temporary contract	0.040 (0.117)	1.041	-0.340 (0.000)	0.711
Private sector	1.123 (0.000)	3.075	-0.554 (0.000)	0.574
Years of studies	0.324 (0.000)	1.383	-0.069 (0.000)	0.933
GDP growth rate	-0.032 (0.002)	0.969	-0.047 (0.033)	0.954
Constant	-5.568 (0.000)		-1.779 (0.000)	
Observations	81204			
Percent correctly predicted	75.42%			
Maximum likelihood	-42655.331			
Pseudo R2	0.187			

p-values in parenthesis

Source: Labour Force Survey

Table 2.3. Multinomial logit for adeqzcy between education and occupation. Mean (constant interval).

Multinomial Logit for adequacy between education and occupation				
Mean (yearly interval)				
	OVEREDUCATION		UNDEREDUCATION	
	coefficient	exp(B)	coefficient	exp(B)
Male	0.546 (0.000)	1.727	-0.408 (0.000)	0.665
Age 31-40	-0.242 (0.000)	0.785	0.054 (0.169)	1.056
Age 41-50	-0.547 (0.000)	0.579	0.308 (0.000)	1.361
Age51-64	-0.926 (0.000)	0.396	0.257 (0.000)	1.293
Temporary contract	0.050 (0.078)	1.051	-0.199 (0.000)	0.819
Private sector	1.239 (0.000)	3.452	-0.319 (0.000)	0.727
Years of studies	0.407 (0.000)	1.502	-0.184 (0.000)	0.832
GDP growth rate	0.051 (0.000)	1.052	-0.311 (0.000)	0.733
Constant	-7.221 (0.000)		0.432 (0.000)	
Observations	81204			
Percent correctly predicted	76.61%			
Maximum likelihood	-44569.447			
Pseudo R2	0.220			

p-values in parenthesis
Source: Labour Force Survey

Table 2.4. Multinomial logit for adequacy between education and occupation. Mean (yearly interval).

Given the difficulties in constructing a reliable measure to follow the evolution of the degree of adjustment across time between job requirements and workers' qualifications, we will opt for the second approach to measuring job match quality (Jovanovic, 1979) and define a job match as an "experienced good". However, we will not use tenure in the job as a proxy for job match quality. The Spanish labour market, as well as the available dataset, the LFS, present some features that suggest an alternative proxy. The Spanish labour market has been characterized in the last two decades by a high degree of duality. In 1984 firms were allowed to hire temporary workers for non-seasonal activities. Since then most new hirings have been registered as temporary contracts¹⁶. In fact, temporary contracts have become the "port of entrance" to almost all jobs¹⁷: firms hire workers on a temporary basis and only after checking the worker's ability and/or reaching the end of the legal time limit of the temporary relationship, do firms convert the temporary contract into a permanent one (Güell and Petrongolo, 2003).

¹⁶Temporary contracts, as opposed to permanent contracts, last for a fixed amount of time and the firm does not have to pay the worker any indemnity when the contract ends.

¹⁷On average, for the period 1988-2000, a 94% of newly registered contracts are temporary contracts (source: Anuario Estadístico de España).

Moreover, the Spanish LFS presents an important drawback: no identifier exists, neither in the case of contracts nor in the case of individual firms, that allows us to distinguish whether the worker is still in the same firm and working under the same temporary contract. This handicap disqualifies the use of reported or observed contract tenures as a proxy for match quality, since, under the duality of the Spanish labour market, (i) tenure in the firm may be longer than that reported in the contract in question, and (ii) tenure in the firm may last longer despite observing a change to a different contract.

Therefore, due to these circumstances, the conversion of a temporary relationship into a permanent one seems to be a better indicator of whether the match turned out to be of good quality. Only those matches that have turned out to be good will be converted into a permanent match after the probation (screening) period or after the legal time limit.

Güell and Petrongolo (2003) have already studied the determinants of the conversion of a temporary contract into a permanent one. However, their interest is on identifying whether temporary contracts are used as a screening device or as a cheaper hiring alternative. Our interest now is in using contract conversion as a proxy for match quality and identifying whether or not the business cycle, at the point of match creation, has any effect in determining job match quality.

3 The data

The data we use is drawn from the Spanish Labor Force Survey (Encuesta de Población Activa). This survey is carried out every quarter on all the household members of a sample of around 60,000 households. Each quarter one sixth of the households is renewed, thus enabling us to follow individuals for a period of up to six consecutive quarters.

The survey provides information on relevant variables such as type of contract and job tenure. These variables will allow us to determine the date at which the worker enters a temporary job match and whether or not this temporary job is converted into a permanent one.

However there are three drawbacks in the dataset that should be noted. The first one refers to the lack of sufficient identification of the contracts and of the companies in the survey, which makes it more difficult to distinguish job/firm changes. Following Güell and Petrongolo (2003) we use the information reported on the type of contract and on contract tenure to identify job changes. Then, as long as reported job tenures keep on increasing, we assume the worker continues with the same temporary contract. Otherwise we assume he has moved to another firm¹⁸. Moreover since firms rarely hire

¹⁸More precisely, if reported tenures are less than a year, we consider that the individual continues with the same temporary contract whenever self-reported job tenure is strictly greater from one interview to the following. However, if reported tenures are greater

workers for the first time under a permanent contract, we assume that all changes of temporary employment states to permanent employment states are conversions of temporary contracts into permanent contracts within the same firm.

The second drawback refers to the methodological changes in the EPA related to the question of tenure. From 1987:II to 1991:IV, reported tenure measures the time the worker has been in the firm. From 1992:I to 1998:IV, reported tenure measures only the time the worker has been under the current contract. And from 1999:I to 2001:III, the survey provides us with both measures of tenure. It is necessary to take into account these methodological changes when interpreting the results.

Finally, the third drawback refers to the way self-reported tenures are recorded. Since 1999:I, reported tenures have been recorded in months. However up to 1998:IV reported tenures were measured in months only when they were less than one year. Otherwise they were recorded in years. Güell and Petrongolo (2003) have explained in detail the bunching problems that may arise from this aggregation. They have also outlined a rounding method to solve this problem based on assigning a random draw from a uniform distribution to any individual reporting a tenure of at least four quarters when first interviewed. Thus all observations with elapsed duration higher than a year are assigned a random quarter within the year. We will also follow this rounding method¹⁹.

3.1 The sample

Our data covers the cohorts entering the sample during the period 1987:II-2001:III. We select male wage earners aged between 20 and 64 years old who are observed in at least one of the interviews to be working under a temporary contract in the private sector. We exclude females from our analysis because we do not have access to relevant information that may explain the

than a year, we only require that job tenures in each consecutive interview of temporary employment be always higher than a year. Otherwise, we will consider the individual has started a new spell of temporary employment.

Moreover, in order to avoid reporting/measuring errors we allow for two corrections at the end of the temporary spell. We will consider that the individual keeps on with the same temporary match whenever:

- Job tenures are longer than a year but between two interviews of temporary employment the individual reports a job tenure lower than a year.

$$Tenure_i \geq 12 \ \& \ Tenure_{i+1} < 12 \ \& \ Tenure_{i+2} \geq 12$$

- Job tenures fall from one interview to the next but in the third one reported job tenure is longer than 12 months

$$Tenure_{i+1} \leq Tenure_i \ \& \ Tenure_i < 12 \ \& \ Tenure_{i+2} \geq 12$$

¹⁹We use this rounding method for the whole sample period.

conversion of temporary contracts into permanent ones for female workers (e.g. number of children). We also require that wage earners are neither doing the military service nor following any kind of studies during the interviews we observe. With these restrictions we want to ensure the individual's commitment to the labour market.

In order to avoid correlation across spells we choose the first spell of temporary employment that is observed for each individual, excluding spells starting before 1987. Otherwise, since our focus is on determining the role of the status of the business cycle, when the match is first created, on match quality, we would be biasing our results in favour of the years prior to 1987. We have also excluded those spells of temporary employment that report a tenure longer than fifteen quarters on first observation.

Taking into account these restrictions we end up with a sample of 66412 spells of temporary employment. In the appendix we report two tables of the distribution of the state of exit by year of match formation (Table A.4) and by year of match ending/censoring (Table A.5)

3.2 The variables

We distinguish four broad groups of variables depending on the spell characteristics which they are controlling: individual characteristics, industry characteristics, seasonal characteristics and economy-wide characteristics.

Regarding individual characteristics we require information on male wage earners when the temporary match is created and when the match is converted, renewed or destroyed. Nevertheless, given the number of censored spells (24%) and the number of spells that are already in existence when the worker is first interviewed (40%), this requirement cannot be fulfilled. In fact we only have access to individual characteristics when the wage earner is first observed. The individual characteristics we will control are education attainment, age and marital status. Education attainment is measured through four dummies that take value one when the highest level of education attained by the worker is *primary*, *secondary*, *vocational* or *university* studies. Age is controlled through three dummies, *Age30*, *Age55* and *Age64*, that take value one depending on whether the temporary match was created when the worker was younger than 30, between 31 and 55 or older than 56 years old respectively. Finally, marital status is measured through a dummy variable that takes value one if the worker is *single* when first observed.

Industry characteristics are controlled through four dummies that group the firm's activity into four different sectors: *agriculture*, *manufacturing*, *construction* and *services*. Seasonal characteristics are controlled through four dummies, *seas1*, *seas2*, *seas3* and *seas4*, that take value one depending on whether the spell is in the first, second, third or fourth quarter of the year.

Finally, we construct the variables that control the economy-wide status. We measure the status of the cycle by the rate of change in GDP from the current quarter to the same quarter of the previous year. Since our objective is to measure the role of the business cycle in determining the quality of the job match, we distinguish between the status of the cycle when the match was created, *initial gdp*, and the status of the cycle as the temporary spell evolves, *gdp*²⁰. We also construct four dummies *nd8792*, *nd9294*, *nd9597* and *nd9701* that intend to capture the effect of the different regulatory environments regarding temporary contracts and the incentives to convert them into permanent ones²¹.

A table of summary statistics (Table A.3) is displayed in the appendix.

4 The Econometric model

4.1 Specification of the hazard without unobserved heterogeneity

The LFS allows us to observe individuals quarterly by providing information on the employment status of the worker at both ends of the quarter. However it does not give a detailed description of what is happening with the worker's temporary contract during the quarter. Even though more than one latent event is possible within a quarter (becoming non-employed, signing a temporary contract with a new firm, or signing a permanent contract with the same firm) we will only observe one of the three possible latent alternatives. Therefore, although the nature of the process of conversion of temporary contracts into permanent ones is most likely to be continuous, we are restricted to work with discrete multiple-risk models.

Let's denote by T the discrete random variable representing the observed time at which the temporary employment spell ends

$$T = \min \{T_U^*, T_T^*, T_P^*\}$$

where T_U^*, T_T^*, T_P^* are the three duration variables for each of the three latent exit alternatives: non-employment, a temporary contract with a different firm and a permanent contract.

We are interested in modelling the conditional probability of exiting towards a permanent contract. Let's assume that the transition towards a permanent contract follows a continuous process with proportional hazard

$$\theta_{pi}(t, X_P) = \theta_0(t) \exp \left(x'_{pi} \beta_p \right)$$

²⁰ An alternative approach would be controlling the cycle through unemployment rates. However, the sample shows a high correlation (0.80) between *initial unemployment* and *current unemployment rates*.

²¹ See Güell and Petrongolo (2003) for a summary of regulatory changes regarding the legislation on temporary contracts.

where X_P is the vector of time-invariant explanatory variables, β_p is the vector of unknown coefficients and $\theta_0(t)$ is the baseline hazard function which is common to all persons (it does not depend on X_P).

Then the discrete conditional hazard function of exiting towards a permanent contract can be written as

$$h_{pi}(t) = pr(T_P^* \in [t-1, t) / T_P^* \geq t-1) = 1 - \exp \left[-\exp \left(x'_{pi} \beta_P + \gamma_t \right) \right]$$

where γ_t is the log of the integrated baseline hazard θ_0 over the interval $[t-1, t)$. We will assume γ_t can differ within each duration interval²², leading us to estimate a semiparametric duration model.

Following Narendranathan and Stewart (1993) and Bover and Gómez (1999) we can estimate the cause-specific hazard rate of a multiple-risk model using single-risk methods where durations finishing for other causes are treated as censored²³.

The conditional log-likelihood function for exit towards a permanent contract can then be written as

$$\begin{aligned} \log L_P = & \sum_{i=1}^n \{c_i D_{Pi} \left[\log h_{pi}(T_i) + \sum_{t=1}^{T_i-1} \log(1 - h_{pi}(t)) \right] + \\ & ((D_{Ui} + D_{Ti}) c_i + (1 - c_i)) \sum_{t=1}^{T_i} \log(1 - h_{pi}(t)) \} \end{aligned}$$

where c_i is an indicator that takes value zero if the spell is censored, and D_{iU} , D_{iT} and D_{iP} are indicators of whether the temporary employment spell ends with a spell of unemployment, with a new temporary contract or with a new permanent contract respectively. Note that exits towards unemployment or a new temporary contract are treated as censored spells.

In order to have access to longer temporary employment spells, and since we can only observe individuals for no more than 6 quarters, we follow Güell and Petrongolo (2003) and include in our sample individuals whose spell of unemployment had already started before they were first interviewed. Therefore, in order to avoid stock sample bias, we have to condition exit rates on the probability of the spell surviving up to the time of the first interview, t_0 . The log-likelihood function is rewritten as

$$\begin{aligned} \log L_P = & \sum_{i=1}^n \{c_i D_{Pi} \left[\log h_{pi}(T_i) + \sum_{t=t_{i0}+1}^{T_i-1} \log(1 - h_{pi}(t)) \right] + \\ & ((D_{Ui} + D_{Ti}) c_i + (1 - c_i)) \sum_{t=t_{i0}+1}^{T_i} \log(1 - h_{pi}(t)) \} \end{aligned}$$

²²We assume that γ_{14} covers all observations longer than fourteen quarters.

²³This approach depends on the independence of the latent hazard rates of exit to the alternative destinations.

At this stage we follow Allison (1982) and Jenkins (1995) and rewrite the model as a binary choice model²⁴. In a duration model we are dealing with a sequence of time where we observe, at each time unit, whether the worker remains with the same temporary contract or changes his employment status. Hence “the discrete duration model can be regarded as a sequence of binary choice equations defined on the survivor population at each duration” (see Bover, 1996). Each individual can then be seen as contributing n_i observations, one for each quarter his spell lasts. This amounts to form a sample of size $N = \sum_i n_i$ observations.

Let y_{pit} be an indicator variable that takes value 1 if the spell of temporary employment of individual i converts into a permanent contract in the t -th interval and takes value 0 otherwise:

$$y_{pit} = \mathbf{1}(T_i \in [t - 1, t))$$

Then, in the case of censored spells $y_{pit} = 0$ for all spell months, and in the case of non censored spells $y_{pit} = 0$ for all spell months but the exit month. The log-likelihood can then be rewritten as

$$L_P(\theta) = \sum_{i=1}^n \sum_{t=1}^{T_i} \{y_{pit} \log h_{pit} + (1 - y_{pit}) \log(1 - h_{pit})\}$$

where θ is the vector of parameters to estimate. Substituting the hazard rate by the expression obtained in (3), yields that $\theta = \begin{bmatrix} \gamma_t \\ \beta_p \end{bmatrix}$.

4.2 Specification of the hazard with unobserved heterogeneity

In the model above it is assumed that the explanatory variables considered summarize all the differences among individuals. However this may not be the case as we may have omitted some variables that were not collected in the dataset, e.g. ability. Not taking into account this unobserved heterogeneity²⁵ may add bias to our results.

In order to capture unobserved individual heterogeneity we introduce a random variable ε . Following Jenkins(1997) the discrete time hazard rate for each person in each duration interval $[t - 1, t)$ can then be written as:

$$h_{pi}(t) = 1 - \exp \left\{ -\varepsilon_i \exp (\beta_p' x_{pi} + \gamma_t) \right\}$$

where ε_i is a positive valued random variable that is assumed to follow a Gamma distribution function with unit mean and finite variance. Generally

²⁴The main advantage of this transformation is the wider availability of statistical packages to estimate binary choice models.

²⁵Another source of heterogeneity may be measurement errors in observed survival times or explanatory variables

it is required that the unobserved heterogeneity term is distributed independently of t and X . However in the framework of a competing risk model we also need to assume that the random disturbance terms in each of the cause-specific hazards are independent of each other (Narendranathan and Stewart, 1993).

The log-likelihood (Jenkins, 1997) then becomes

$$\log L_P = \sum_{i=1}^n \log [((D_{Ui} + D_{Ti})c_i + (1 - c_i))A_{pi} + c_i D_{pi} B_{pi}]$$

with

$$A_{pi} = \left[1 + \sigma^2 \sum_{t=t_{i0}+1}^{T_i} \exp(x_{pi}'\beta_p + \gamma_t) \right]^{-\frac{1}{\sigma^2}}$$

$$B_{pi} = \begin{cases} \left[1 + \sigma^2 \sum_{t=t_{i0}+1}^{T_i-1} \exp(x_{pi}'\beta_p + \gamma_t) \right]^{-\frac{1}{\sigma^2}} - A_{pi} & \text{if } T_i > 1 \\ 1 - A_{pi} & \text{if } T_i = 1 \end{cases}$$

where c_i and γ_t are the usual censoring indicator and the function describing duration dependence respectively, and σ^2 is the variance of the gamma-distributed random variable.

5 Discussion of the results

The results for the estimation of the duration model discussed in the previous section are presented in Table A.6. The estimates refer to the whole sample of male wage earners aged between 20 and 64 years old. The estimations displayed in columns (1) to (3) differ according to the variables used to isolate the role of the business cycle. In the first column we only control for the current state of the cycle. In the second column we display the estimates when we control for the current state of the cycle, as well as for the state of the cycle at the time the temporary job match is created. Finally, in the third column we also introduce three dummy variables that attempt to cover the different regulatory periods regarding the legislation on temporary contracts.

Initially (column (1)) we observe that the rate of conversion of temporary contracts into permanent contracts appears to be procyclical. Hence the quality of job matches will increase as the current state of the business cycle improves. However, when we also take into account the state of the cycle when the temporary contract is created (column (2)), we obtain that the role of the current cycle is no longer significant. In fact we observe that the relevant variable is the state of the business cycle at the moment of job creation. This result remains valid when we introduce the dummy variables that control for the different regulatory periods (column (3)).

In view of these results we can argue that, once we have isolated the role of the different states of the cycle, temporary matches created during periods of economic expansion are more likely to be converted into permanent relationships between the employer and the employee than matches created in periods of recession. Therefore job matches created during expansions turn out to be of better quality than job matches created during economic downturns (see also Figure A.1). This result is in line with that obtained in Bowlus (1995) and Centeno (2003) for the US economy.

This higher rate of mismatching during recessions could be explained by two different arguments. On the one hand, it may be due to general mismatching, i.e., it takes place across all matches, no matter what their characteristics. The reason may perhaps be due to the greater difficulties experienced during economic downturns in revealing the asymmetric information that employers and employees have prior to match formation. On the other hand, we can argue that the higher mismatching during recessions is attributable to a “stop-gap” job phenomenon. During recessions it is more difficult for unemployed workers to find jobs that match their skills. Therefore in order to leave unemployment they may be willing to accept jobs in occupations that require lower skills while waiting for better opportunities to appear when the economy improves.

In order to check which of these hypothesis explains the higher rate of mismatching in recessions we construct two subsamples depending on the occupational category of the matches (Bowlus, 1995). The first subsample includes matches in occupations we consider more likely to be used as “stop-gap” jobs. These are clerks, store assistants and jobs in the service industry. The second subsample includes occupations such as professionals, technicians and managers which require more specific skills.

The results in Tables A.7 and A.8 show that the status of the business cycle when the temporary contract is created plays a positive role in determining the quality of “stop-gap” jobs (see also Figure A.2). However the quality of the non “stop-gap” jobs does not seem to be affected by the initial but by the current status of the cycle.

Contrary to what was obtained for the US economy (Bowlus, 1995), this result suggests that the higher rate of mismatching during recessions is not caused by a general mismatching phenomenon. Instead, it appears to be caused by the “stop-gap” job phenomenon. During recessions workers are more willing to accept transitory lower qualified jobs while waiting for the business cycle to pick up.

The Spanish labour market has been characterized in the last decade by a progressive movement of qualified entrants towards occupations that require lower qualification levels. This process has been referred to as the “crowding-out” of lower educated by more highly educated workers (Dolado et al., 2000). We would expect that this “crowding-out” effect increases especially during recessions and that qualified workers end up participating

in matches that require lower qualifications just in the hope of achieving a better match during the next economic boom (“stop-gap” jobs).

We can also highlight the following results. Regarding the regulatory dummies, we obtain that subsequent reforms have reduced the rate of conversion of temporary contracts into permanent ones and hence, we could argue, the quality of the matches created under temporary contracts²⁶. This result becomes less clear in the case of non “stop-gap” jobs.

Secondly, the educational dummies show that the quality of the match increases with the level of education of the employee. Again, the case of non “stop-gap” jobs does not follow this pattern. Thus, in this case education does not seem to be a key determinant of the quality of the match.

Thirdly, matches with workers aged between 30 and 55 years old are of better quality than matches with younger workers. However this positive effect of middle-aged workers disappears as their tenure in the temporary contract increases (column (3)). Note here that in the case of “stop-gap” jobs age is no longer a determinant variable for the quality of the match.

Finally, results obtained when taking into account unobserved heterogeneity remain roughly the same²⁷ (see Tables A.9, A.10 and A.11). The only difference is in the pattern of duration dependence: the slope of the pattern and the probability of conversion into a permanent contract at each time interval turn out to be higher compared to the case where there is no control for unobserved heterogeneity.

6 Conclusions

This paper has analysed the role played by the business cycle phase, at the time of job creation, in determining job match quality in the Spanish labour market during 1987-2001. Job match quality has traditionally been proxied by two measures: the degree of educational adjustment to occupational requirements, and the length of tenure in the job. Given our data limitations and the duality of the Spanish labour market we have opted for a different proxy for job match quality: the conversion of temporary into permanent contracts. Under this approach good matches will be converted into permanent contracts while bad matches will not.

Results have shown that temporary matches created during economic expansions are more likely to be converted into permanent relationships between the employer and the employee than those matches created during economic recessions. This result is in line with the evidence for the US

²⁶ Al comentar estas dummies se puede comentar lo del cambio metodológico que comentábamos en el apartado 3. El cambio tendería a sesgar positivamente el efecto de los tramos 92-94 y 95-97. A pesar de esta sesgo positivo, la calidad disminuye durante estos períodos.

²⁷ Following Jenkins (2002) “the effects of unobserved heterogeneity are mitigated and thence estimates more robust, if the analyst uses a flexible baseline hazard specification”.

economy: match quality is positively related with the status of the cycle when the match is created.

However, contrary to what has been obtained for the US economy, our results suggest that the higher Spanish rate of mismatching during recessions is not caused by a general mismatching phenomenon but instead appears to be caused by a “stop-gap” job phenomenon: during recessions workers are more willing to accept transitory low qualified jobs while waiting for the economy to recover.

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A Tables and Figures

Multinomial Logit for adequacy between education and occupation				
Mode (constant interval)				
	OVEREDUCATION		UNDEREDUCATION	
	coefficient	exp(B)	coefficient	exp(B)
Male	0.184 (0.000)	1.202	-0.352 (0.000)	0.703
Age 31-40	-0.679 (0.000)	0.507	-0.605 (0.000)	0.546
Age 41-50	-1.52 (0.000)	0.219	-0.833 (0.000)	0.435
Age51-64	-2.391 (0.000)	0.092	-1.18 (0.000)	0.307
Temporary contract	0.061 (0.005)	1.063	-0.086 (0.014)	0.918
Private sector	1.173 (0.000)	3.231	0.332 (0.000)	1.394
Years of studies	0.231 (0.000)	1.260	0.175 (0.000)	1.191
GDP growth rate	-0.163 (0.000)	0.850	-0.165 (0.000)	0.848
Constant	-2.011 (0.000)		-2.268 (0.000)	
Observations	81204			
Percent correctly predicted	72.73%			
Maximum likelihood	-62060.076			
Pseudo R2	0.161			

p-values in parenthesis

Source: Labour Force Survey

Table A.1. Multinomial logit for adequacy between education and occupation. Mode (constant interval).

Multinomial Logit for adequacy between education and occupation				
Mode (yearly interval)				
	OVEREDUCATION		UNDEREDUCATION	
	coefficient	exp(B)	coefficient	exp(B)
Male	0.364 (0.000)	1.439	-0.349 (0.000)	0.705
Age 31-40	-0.591 (0.000)	0.554	-0.382 (0.000)	0.683
Age 41-50	-1.364 (0.000)	0.256	-0.373 (0.000)	0.689
Age51-64	-2.187 (0.000)	0.112	-0.568 (0.000)	0.567
Temporary contract	0.058 (0.009)	1.060	-0.166 (0.000)	0.847
Private sector	1.018 (0.000)	2.767	0.15 (0.000)	1.162
Years of studies	0.228 (0.000)	1.256	0.07 (0.000)	1.073
GDP growth rate	-0.055 (0.000)	0.947	-0.223 (0.000)	0.800
Constant	-2.652 (0.000)		-0.815 (0.000)	
Observations	81204			
Percent correctly predicted	67.51%			
Maximum likelihood	-68187.971			
Pseudo R2	0.133			

p-values in parenthesis

Source: Labour Force Survey

Table A.2. Multinomial logit for adequacy between education and occupation. Mode (yearly interval).

SUMMARY STATISTICS						
Variable	WHOLE SAMPLE		STOPGAP-JOBS		NON STOPGAP-JOBS	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Duration	3.544	3.261	3.423	3.076	3.738	3.312
Censored	0.137	0.344	0.166	0.372	0.181	0.385
INDIVIDUAL CHARACTERISTICS						
Age 20-30	0.496	0.500	0.612	0.487	0.543	0.498
Age 31-55	0.454	0.498	0.361	0.480	0.413	0.492
Age 56-64	0.049	0.216	0.027	0.161	0.043	0.203
Primary Studies	0.475	0.499	0.309	0.462	0.185	0.388
Secondary Studies	0.369	0.483	0.489	0.500	0.262	0.440
Vocational Studies	0.119	0.324	0.152	0.359	0.175	0.380
University Studies	0.036	0.186	0.049	0.216	0.379	0.485
Single	0.475	0.499	0.587	0.492	0.562	0.496
SECTORAL CHARACTERISTICS						
Agriculture	0.173	0.378	0.025	0.156	0.199	0.399
Construction	0.338	0.473	0.025	0.157	0.073	0.260
Manufacturing	0.186	0.389	0.059	0.237	0.157	0.364
Services	0.303	0.459	0.890	0.312	0.571	0.495
Number of observations	66412		11127		3980	

Table A.3. Summary statistics.

DISTRIBUTION OF FIXED-TERM CONTRACTS BY STATE OF EXIT AND QUARTER OF MATCH FORMATION (Percentage)					
	SAME TEMPORARY CONTRACT	NON EMPLOYMENT	PERMANENT CONTRACT	NEW TEMPORARY CONTRACT	# OF SPELLS
1987:II	18.86	26.37	31.24	23.53	493
1988:II	23.58	24.78	26.67	24.98	1001
1989:II	23.80	20.61	21.42	34.17	1349
1990:II	24.55	23.40	17.92	34.12	1222
1991:II	16.91	28.60	15.29	39.21	1112
1992:II	17.29	27.95	11.63	43.13	1238
1993:II	14.16	29.30	9.77	46.77	1116
1994:II	17.91	24.78	10.64	46.67	1457
1995:II	16.60	26.98	10.05	46.37	1542
1996:II	20.41	21.17	9.45	48.97	1450
1997:II	22.96	20.09	9.38	47.58	1568
1998:II	34.14	19.96	12.66	33.24	1453
1999:II	43.22	24.98	9.88	21.92	1113
2000:II	40.95	28.33	39.12	21.60	713
2001:II	86.90	5.95	4.76	2.38	84

Table A.4. Distribution of fixed-term contracts by state of exit and quarter of match formation.

DISTRIBUTION OF FIXED-TERM CONTRACTS BY STATE OF EXIT AND QUARTER OF CONTRACT ENDING/TRANSFORMATION/CENSORING (Percentage)					
	SAME TEMPORARY CONTRACT	NON EMPLOYMENT	PERMANENT CONTRACT	NEW TEMPORARY CONTRACT	# OF SPELLS
1987:II	0.00	45.79	29.91	24.30	107
1988:II	11.31	24.43	35.14	29.11	663
1989:II	21.41	21.12	26.13	31.34	1018
1990:II	24.81	19.53	23.55	32.10	1193
1991:II	27.25	23.01	21.65	28.10	1178
1992:II	20.56	22.97	12.20	44.28	1328
1993:II	17.16	25.70	9.87	47.28	1358
1994:II	17.53	26.67	9.88	45.91	1346
1995:II	17.46	24.98	9.74	47.82	1581
1996:II	18.59	20.01	9.90	51.50	1334
1997:II	19.02	21.33	8.07	51.59	1388
1998:II	22.26	18.40	8.64	50.70	1424
1999:II	39.04	26.24	14.92	19.80	1086
2000:II	45.10	22.51	12.86	19.53	1244

Table A.5. Distribution of fixed-term contracts by state of exit and quarter of contract ending/transformation/censoring.

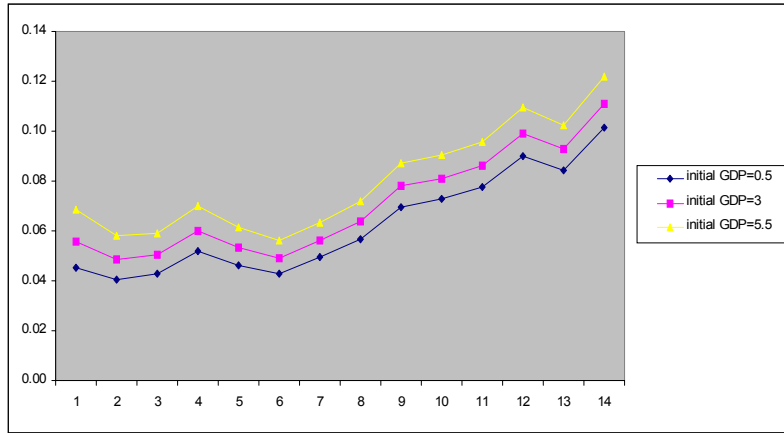


Figure A.1: Predicted hazard rate by the status of the cycle when first job creation. Whole Sample.

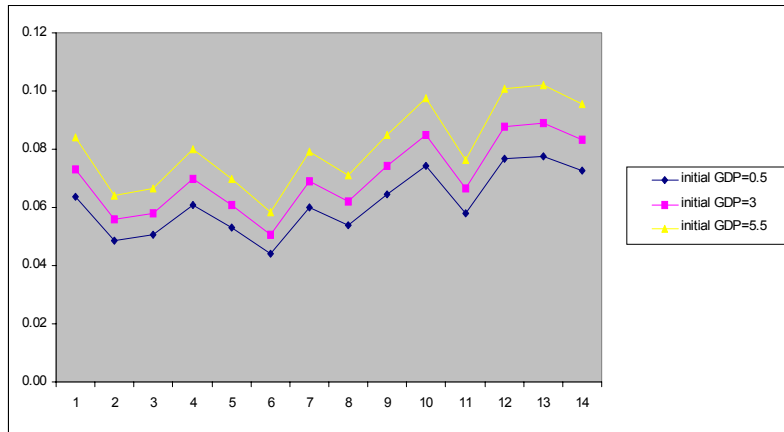


Figure A.2. Predicted hazard-rate by status of the cycle when first job creation. Stop-gap jobs.

ESTIMATES OF LOGISTIC HAZARDS						
Variable	Male					
	Whole sample (1)		Whole sample (2)		Whole sample (3)	
	Coeff	p-value	Coeff	p-value	Coeff	p-value
INDIVIDUAL CHARACTERISTICS						
Age55	0.067	0.080	0.069	0.071	0.184	0.000
Age55 x log Dur	-0.147	0.000	-0.142	0.000	-0.130	0.000
Age 64	-0.093	0.109	-0.082	0.158	0.031	0.588
Primary studies	-0.125	0.014	-0.131	0.010	-0.316	0.000
Secondary studies	-0.250	0.000	-0.249	0.000	-0.303	0.000
Vocational studies	-0.120	0.026	-0.118	0.030	-0.143	0.008
Single	-0.252	0.000	-0.254	0.000	-0.225	0.000
SECTORAL DUMMIES						
Agriculture	-0.211	0.000	-0.210	0.000	-0.307	0.000
Agriculture x log Dur	0.141	0.000	0.122	0.000	0.102	0.004
Manufacture	-0.149	0.000	-0.147	0.000	-0.095	0.001
Construction	-0.534	0.000	-0.537	0.000	-0.543	0.000
Construction x log Dur	-0.166	0.000	-0.161	0.000	-0.125	0.000
ECONOMY WIDE CHARACTERISTICS						
gdp	0.088	0.000	-0.009	0.663	0.002	0.913
gdp x log Dur	-0.033	0.000	0.004	0.689	0.028	0.012
initial gdp			0.095	0.000	0.086	0.000
initial gdp x log Dur			-0.007	0.521	-0.041	0.000
Tramo 1987-1992					0.897	0.000
Tramo 1993-1994					0.543	0.000
Tramo 1995-1997:II					0.228	0.000
SEASONAL DUMMIES						
Seas1	-0.052	0.088	-0.044	0.144	-0.062	0.041
Seas2	0.022	0.463	0.022	0.457	0.001	0.968
Seas3	0.030	0.317	0.026	0.377	0.046	0.122
DURATION DUMMIES						
d1	-2.470	0.000	-2.465	0.000	-2.902	0.000
d2	-2.555	0.000	-2.624	0.000	-3.031	0.000
d3	-2.473	0.000	-2.589	0.000	-2.985	0.000
d4	-2.291	0.000	-2.436	0.000	-2.794	0.000
d5	-2.384	0.000	-2.570	0.000	-2.916	0.000
d6	-2.446	0.000	-2.662	0.000	-2.997	0.000
d7	-2.277	0.000	-2.511	0.000	-2.860	0.000
d8	-2.121	0.000	-2.373	0.000	-2.724	0.000
d9	-1.913	0.000	-2.179	0.000	-2.512	0.000
d10	-1.870	0.000	-2.146	0.000	-2.471	0.000
d11	-1.804	0.000	-2.086	0.000	-2.405	0.000
d12	-1.675	0.000	-1.960	0.000	-2.256	0.000
d13	-1.764	0.000	-2.056	0.000	-2.325	0.000
d14	-1.617	0.000	-1.907	0.000	-2.134	0.000
Number of observations:	151233		151233		151233	
Variance						
Log likelihood:	-33739.572		-33693.371		-33120.011	

Table A.6. Estimates of logistic hazards. Whole sample.

ESTIMATES OF LOGISTIC HAZARDS						
Variable	Male					
	No Stopgap-Job (1)		No Stopgap-Job (2)		No Stopgap-Job (3)	
	Coeff	p-value	Coeff	p-value	Coeff	p-value
INDIVIDUAL CHARACTERISTICS						
Age55	0.275	0.056	0.267	0.064	0.353	0.014
Age55 x log Dur	-0.235	0.013	-0.227	0.016	-0.236	0.012
Age 64	-0.254	0.309	-0.252	0.312	-0.225	0.367
Primary studies	-0.251	0.083	-0.243	0.093	-0.113	0.431
Secondary studies	-0.086	0.379	-0.083	0.398	0.005	0.961
Vocational studies	0.003	0.979	0.010	0.920	0.056	0.589
Single	-0.202	0.041	-0.212	0.033	-0.174	0.078
SECTORAL DUMMIES						
Agriculture	0.036	0.766	0.024	0.839	0.036	0.759
Manufacture	0.156	0.119	0.153	0.126	0.204	0.042
Construction	-0.219	0.130	-0.220	0.127	-0.223	0.122
ECONOMY WIDE CHARACTERISTICS						
gdp	0.060	0.015	0.034	0.257	0.089	0.012
initial gdp			0.045	0.108	-0.013	0.675
Tramo 1987-1992					0.891	0.000
Tramo 1993-1994					0.160	0.437
Tramo 1995-1997:II					0.158	0.178
SEASONAL DUMMIES						
Seas1	-0.105	0.345	-0.096	0.387	-0.128	0.251
Seas2	0.014	0.895	0.019	0.858	-0.011	0.921
Seas3	0.127	0.226	0.127	0.224	0.132	0.206
DURATION DUMMIES						
d1	-2.762	0.000	-2.819	0.000	-3.141	0.000
d2	-2.647	0.000	-2.706	0.000	-3.015	0.000
d3	-2.769	0.000	-2.828	0.000	-3.138	0.000
d4	-2.448	0.000	-2.508	0.000	-2.788	0.000
d5	-2.695	0.000	-2.767	0.000	-3.042	0.000
d6	-2.626	0.000	-2.700	0.000	-3.010	0.000
d7	-3.282	0.000	-3.360	0.000	-3.663	0.000
d8	-2.233	0.000	-2.309	0.000	-2.640	0.000
d9	-2.443	0.000	-2.515	0.000	-2.842	0.000
d10	-1.914	0.000	-1.984	0.000	-2.302	0.000
d11	-1.771	0.000	-1.836	0.000	-2.156	0.000
d12	-1.796	0.000	-1.861	0.000	-2.142	0.000
d13	-2.420	0.000	-2.469	0.000	-2.769	0.000
d14	-2.146	0.000	-2.199	0.000	-2.463	0.000
Number of observations:	9326		9326		9326	
Variance						
Log likelihood:	-2494.726		-2493.441		-2458.090	

Table A.7. Estimates of logistic hazards. No stop-gap jobs.

ESTIMATES OF LOGISTIC HAZARDS						
Variable	Male					
	Stopgap-Job (1)		Stopgap-Job (2)		Stopgap-Job (3)	
	Coeff	p-value	Coeff	p-value	Coeff	p-value
INDIVIDUAL CHARACTERISTICS						
Age55	-0.113	0.068	-0.093	0.135	0.013	0.837
Age 64	-0.047	0.749	-0.019	0.899	0.069	0.642
Primary studies	-0.201	0.054	-0.200	0.055	-0.316	0.002
Secondary studies	-0.255	0.010	-0.237	0.016	-0.283	0.004
Vocational studies	-0.210	0.055	-0.186	0.089	-0.173	0.115
Single	-0.425	0.000	-0.423	0.000	-0.400	0.000
Single x log Dur	0.138	0.014	0.133	0.017	0.131	0.020
SECTORAL DUMMIES						
Agriculture	0.269	0.032	0.221	0.079	0.059	0.641
Manufacture	0.253	0.073	0.270	0.055	0.208	0.139
Manufacture x log Dur	-0.165	0.137	-0.168	0.130	-0.171	0.123
Construction x log Dur	-0.849	0.000	-0.826	0.000	-0.855	0.000
ECONOMY WIDE CHARACTERISTICS						
gdp	0.053	0.000	-0.028	0.094	-0.001	0.743
initial gdp			0.123	0.000	0.057	0.002
Tramo 1987-1992					0.721	0.000
Tramo 1993-1994					0.202	0.078
Tramo 1995-1997:II					0.126	0.128
SEASONAL DUMMIES						
Seas1	-0.176	0.009	-0.164	0.015	-0.173	0.010
Seas2	-0.178	0.007	-0.181	0.006	-0.195	0.003
Seas3	-0.087	0.170	-0.093	0.143	-0.077	0.226
DURATION DUMMIES						
d1	-1.991	0.000	-2.151	0.000	-2.344	0.000
d2	-2.331	0.000	-2.492	0.000	-2.662	0.000
d3	-2.291	0.000	-2.464	0.000	-2.649	0.000
d4	-2.145	0.000	-2.312	0.000	-2.475	0.000
d5	-2.264	0.000	-2.461	0.000	-2.626	0.000
d6	-2.429	0.000	-2.648	0.000	-2.824	0.000
d7	-2.097	0.000	-2.326	0.000	-2.517	0.000
d8	-2.189	0.000	-2.445	0.000	-2.636	0.000
d9	-2.034	0.000	-2.289	0.000	-2.456	0.000
d10	-1.900	0.000	-2.160	0.000	-2.318	0.000
d11	-2.164	0.000	-2.421	0.000	-2.577	0.000
d12	-1.853	0.000	-2.133	0.000	-2.294	0.000
d13	-1.884	0.000	-2.168	0.000	-2.285	0.000
d14	-2.002	0.000	-2.262	0.000	-2.360	0.000
Number of observations:	24113		24113		24113	
Variance						
Log likelihood:	-6448.309		-6423.150		-6343.409	

Table A.8. Estimates of logistic hazards. Stop-gap jobs.

ESTIMATES OF LOGISTIC HAZARDS						
Unobserved Heterogeneity						
Male						
Variable	Whole sample (1)		Whole sample (2)		Whole sample (3)	
	Coeff	p-value	Coeff	p-value	Coeff	p-value
INDIVIDUAL CHARACTERISTICS						
Age55	0.082	0.076	0.086	0.066	0.235	0.000
Age55 x log Dur	-0.170	0.000	-0.162	0.000	-0.155	0.000
Age 64	-0.105	0.153	-0.089	0.233	0.038	0.616
Primary studies	-0.176	0.012	-0.187	0.009	-0.425	0.000
Secondary studies	-0.337	0.000	-0.337	0.000	-0.394	0.000
Vocational studies	-0.178	0.018	-0.174	0.022	-0.186	0.014
Single	-0.306	0.000	-0.312	0.000	-0.265	0.000
SECTORAL DUMMIES						
Agriculture	-0.277	0.000	-0.278	0.000	-0.393	0.000
Agriculture x log Dur	0.232	0.000	0.202	0.000	0.154	0.002
Manufacture	-0.215	0.000	-0.216	0.000	-0.140	0.000
Construction	-0.567	0.000	-0.571	0.000	-0.604	0.000
Construction x log Dur	-0.309	0.000	-0.318	0.000	-0.276	0.000
ECONOMY WIDE CHARACTERISTICS						
gdp	0.084	0.000	-0.011	0.666	-0.008	0.733
gdp x log Dur	-0.027	0.001	0.001	0.937	0.031	0.025
initial gdp			0.095	0.000	0.082	0.001
initial gdp x log Dur			0.027	0.068	-0.012	0.404
Tramo 1987-1992					1.206	0.000
Tramo 1993-1994					0.673	0.000
Tramo 1995-1997:II					0.294	0.000
SEASONAL DUMMIES						
Seas1	-0.059	0.065	-0.049	0.130	-0.079	0.015
Seas2	0.020	0.526	0.023	0.162	-0.015	0.636
Seas3	0.028	0.373	0.026	0.406	0.048	0.126
DURATION DUMMIES						
d1	-2.230	0.000	-2.218	0.000	-2.782	0.000
d2	-2.177	0.000	-2.286	0.000	-2.796	0.000
d3	-1.990	0.000	-2.174	0.000	-2.664	0.000
d4	-1.687	0.000	-1.913	0.000	-2.353	0.000
d5	-1.673	0.000	-1.962	0.000	-2.394	0.000
d6	-1.704	0.000	-2.043	0.000	-2.475	0.000
d7	-1.575	0.000	-1.954	0.000	-2.388	0.000
d8	-1.409	0.000	-1.820	0.000	-2.255	0.000
d9	-1.153	0.000	-1.590	0.000	-2.005	0.000
d10	-1.085	0.000	-1.537	0.000	-1.945	0.000
d11	-0.975	0.000	-1.433	0.000	-1.838	0.000
d12	-0.814	0.000	-1.269	0.000	-1.651	0.000
d13	-0.770	0.000	-1.225	0.000	-1.593	0.000
d14	-0.449	0.000	-0.904	0.000	-1.228	0.000
Number of observations:	151233		151233		151233	
Probability test statistic	1.866e-84		7.622e-96		3.714e-108	
Log likelihood:	-33549.976		-33477.616		-32875.967	

Table A.9. Estimates of logistic hazards. Whole sample. Unobserved heterogeneity.

ESTIMATES OF LOGISTIC HAZARDS						
Unobserved Heterogeneity						
Male						
Variable	No Stopgap-Job (1)		No Stopgap-Job (2)		No Stopgap-Job (3)	
	Coeff	p-value	Coeff	p-value	Coeff	p-value
INDIVIDUAL CHARACTERISTICS						
Age55	0.337	0.045	0.329	0.052	0.441	0.009
Age55 x log Dur	-0.262	0.024	-0.252	0.031	-0.269	0.021
Age 64	-0.330	0.270	-0.337	0.264	-0.241	0.424
Primary studies	-0.353	0.043	-0.345	0.049	-0.189	0.277
Secondary studies	-0.143	0.243	-0.139	0.261	-0.013	0.915
Vocational studies	0.024	0.853	0.037	0.778	0.120	0.365
Single	-0.264	0.035	-0.281	0.026	-0.217	0.082
SECTORAL DUMMIES						
Agriculture	0.084	0.565	0.070	0.633	0.083	0.570
Manufacture	0.178	0.163	0.169	0.190	0.220	0.086
Construction	-0.246	0.175	-0.254	0.166	-0.298	0.101
ECONOMY WIDE CHARACTERISTICS						
gdp	0.071	0.014	0.028	0.436	0.084	0.039
initial gdp			0.072	0.051	0.004	0.916
Tramo 1987-1992					1.155	0.000
Tramo 1993-1994					0.189	0.432
Tramo 1995-1997:II					0.163	0.240
SEASONAL DUMMIES						
Seas1	-0.121	0.291	-0.108	0.346	-0.150	0.195
Seas2	-0.006	0.955	0.003	0.980	-0.040	0.722
Seas3	0.114	0.295	0.115	0.289	0.106	0.332
DURATION DUMMIES						
d1	-2.688	0.000	-2.776	0.000	-3.166	0.000
d2	-2.460	0.000	-2.545	0.000	-2.914	0.000
d3	-2.525	0.000	-2.608	0.000	-2.979	0.000
d4	-2.103	0.000	-2.181	0.000	-2.513	0.000
d5	-2.248	0.000	-2.339	0.000	-2.670	0.000
d6	-2.161	0.000	-2.252	0.000	-2.632	0.000
d7	-2.870	0.000	-2.971	0.000	-3.327	0.000
d8	-1.826	0.000	-1.925	0.000	-2.345	0.000
d9	-1.954	0.000	-2.042	0.000	-2.439	0.000
d10	-1.451	0.000	-1.541	0.000	-1.974	0.000
d11	-1.176	0.000	-1.251	0.000	-1.657	0.000
d12	-1.070	0.000	-1.143	0.000	-1.524	0.000
d13	-1.644	0.000	-1.682	0.000	-2.097	0.000
d14	-1.338	0.000	-1.384	0.000	-1.818	0.000
Number of observations:	9326		9326		9326	
Evidence of unobserved heterogeneity	7.110e-06		3.505e-06		1.257e-06	
Log likelihood:	-2484.644		-2482.682		-2446.345	

Table A.10. Estimates of logistic hazards. No stop-gap job. Unobserved heterogeneity.

ESTIMATES OF LOGISTIC HAZARDS						
Unobserved Heterogeneity						
Male						
Variable	Stopgap-Job (1)		Stopgap-Job (2)		Stopgap-Job (3)	
	Coeff	p-value	Coeff	p-value	Coeff	p-value
INDIVIDUAL CHARACTERISTICS						
Age55	-0.095	0.246	-0.081	0.326	0.037	0.655
Age 64	-0.008	0.967	0.011	0.954	0.079	0.692
Primary studies	-0.293	0.042	-0.300	0.039	-0.451	0.002
Secondary studies	-0.357	0.009	-0.350	0.011	-0.402	0.004
Vocational studies	-0.265	0.080	-0.239	0.117	-0.227	0.137
Single	-0.492	0.000	-0.504	0.000	-0.472	0.000
Single x log Dur	0.159	0.033	0.162	0.031	0.162	0.031
SECTORAL DUMMIES						
Agriculture	0.519	0.005	0.486	0.009	0.238	0.199
Manufacture	0.315	0.070	0.338	0.053	0.238	0.174
Manufacture x log Dur	-0.200	0.169	-0.197	0.180	-0.175	0.234
Construction x log Dur	-1.016	0.000	-0.990	0.000	-1.032	0.000
ECONOMY WIDE CHARACTERISTICS						
gdp	0.058	0.000	-0.054	0.013	-0.028	0.214
initial gdp			0.173	0.000	0.089	0.000
Tramo 1987-1992					0.975	0.000
Tramo 1993-1994					0.277	0.046
Tramo 1995-1997:II					0.149	0.142
SEASONAL DUMMIES						
Seas1	-0.184	0.010	-0.169	0.018	-0.188	0.009
Seas2	-0.193	0.006	-0.191	0.007	-0.217	0.002
Seas3	-0.096	0.158	-0.101	0.138	-0.081	0.232
DURATION DUMMIES						
d1	-1.766	0.000	-1.971	0.000	-2.236	0.000
d2	-1.979	0.000	-2.189	0.000	-2.415	0.000
d3	-1.844	0.000	-2.067	0.000	-2.306	0.000
d4	-1.577	0.000	-1.793	0.000	-2.005	0.000
d5	-1.596	0.000	-1.848	0.000	-2.068	0.000
d6	-1.719	0.000	-2.001	0.000	-2.243	0.000
d7	-1.447	0.000	-1.755	0.000	-2.009	0.000
d8	-1.479	0.000	-1.809	0.000	-2.059	0.000
d9	-1.233	0.000	-1.611	0.000	-1.826	0.000
d10	-1.126	0.000	-1.477	0.000	-1.670	0.000
d11	-1.413	0.000	-1.755	0.000	-1.951	0.000
d12	-1.070	0.000	-1.412	0.000	-1.626	0.000
d13	-0.876	0.000	-1.230	0.000	-1.423	0.000
d14	-0.906	0.000	-1.269	0.000	-1.423	0.000
Number of observations:	24113		24113		24113	
Evidence of unobserved heterogeneity	3.012e-21		4.583e-23		3.679e-25	
Log likelihood:	-6403.541		-6374.241		-6289.720	

Table A.11. Estimates of logistic hazards. Stop-gap job. Unobserved heterogeneity.

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