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The long-lasting scar of bad jobs in the Spanish labour market

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The long-lasting scar of bad jobs in the Spanish labour market

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Abstract

Most young Spaniards start their working lives with low wages and highly unstable jobs. Many of them progressively improve their working conditions and move towards better jobs. Yet a relevant fraction get trapped into those low-quality jobs. We refer to this phenomenon as the scar of bad jobs. The purpose of this paper is to analyse the extent and nature of the scar, which helps learn about the hysteresis of bad jobs in Spain. To do so, we use longitudinal administrative records and compute an index to measure the quality of jobs. This is constructed by combining data on labour earnings, number of hours worked and employment rotation. By observing individuals not only at the start of their career, but also five and ten years later, we find that a bad job at the beginning is an important predictor of a bad job five years after, particularly if a bad job stems from working few hours. Additionally, those who escape from bad jobs in the first five years are unlikely to be trapped into them in the long run. Interestingly, the depth of the scar varies along the economic cycle. In particular, the Great Recession severely impacted the future careers of entrants, compared to the pre-crisis workers. Lastly, we identify that women, younger entrants and hospitality workers are more prone to hold their bad jobs in the medium and long term, and hence to be relegated to the lower tail of the income distribution.

Keywords Bad jobs, employment precariousness, quality of employment, scarring effect, social mobility

JEL classification J20, J21, J28, J80, J81, J88

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1. Introduction

The lifetime evolution of job earnings determines the dynamics of most of households' income, and it is a key element to explain the observed income distribution. Many individuals start their working lives with temporary or unstable contracts that often involve relatively low wages. As time permits that productivity be revealed, and workers accumulate experience on the job and gain seniority, those initial conditions improve towards higher wages and more stable contracts. That is, people move towards higher quantiles of the income distribution as an expression of *social mobility* relative to their initial conditions. From this perspective, the low quality of the jobs at the initial phase of the working career might be regarded as an entrance fee, under the expectation that the situation will eventually change. In other words, starting the work experience with a "bad job" might seem acceptable, provided that it is a transitory situation. The question is whether this is actually the case or whether an initial bad job may become a trap for the future, as suggested by Lewchuk et al. (2016) and Campbell and Price (2016).

The purpose of this paper is to analyze the hysteresis of bad jobs in the Spanish labour market for the last few decades. That is, the extent to which starting with a bad job in Spain affects labour opportunities in the future and, hence, the type of social mobility mentioned above. This can be regarded as *the scar of bad jobs*, by analogy to the notion of the scar of unemployment (e.g., Gangi 2006; de Fraja et al. 2017). More specifically, we aim at estimating the role of those factors that affect the probability of remaining in a bad job five and ten years after entering the market. To achieve this goal, we need to deal with three different but intertwined issues. The first involves selecting a database that permits one to follow the workers' employment history; the second requires finding an operational definition of what a bad job is; and the third entails formulating the appropriate econometric models.

Regarding the database, our analysis will rely on the Spanish Continuous Sample of Working Histories (*Muestra Continua de Vidas Laborales*, MCVL). This longitudinal database contains detailed information on individuals' number of hours worked, hourly wages, and the number of contracts signed in a given time-period. Our target population consists of individuals entering the labour market from 1997 onwards and whose age at entry is between 16 and 30. In particular, we observe these individuals at entry and follow them five and ten years later. We want to study the dynamics of the jobs of those who started with a bad job, relative to those who did not.

There are many aspects that determine the quality of a job for an individual, including hourly wages, number of hours worked per period, type of contract, working schedule, training facilities, complementary benefits, chances of job progression, etc. Those aspects, hence, may help defining what a bad job is. We shall focus here on the main determinants of the quality of a job on which we can have yearly data on the workers' labour history: hourly wages, total number of hours worked, and number of contracts per period. Those variables are regarded as the key dimensions of precariousness in the labour market (Rodgers and Rodgers 1989; Leschke and Keune 2008; Kalleberg 2009, 2011; Olsthoorn 2014). On the one hand, low levels of labour income—due to low wages and/or few hours worked—reduce consumption and saving possibilities, which may severely restrict access to housing and credit and so hamper intertemporal substitution, among other implications that go beyond economic factors (children, health, marriage, etc.). On the other hand, the number of contracts per period is a proxy of the stability of the job, an element that also affects households' decisions on the future. Changing frequently from one job to another hinders the accumulation of work experience, besides incurring substantial transition costs. This gives a bad signal to the market, making it more difficult to move towards better jobs. Even if the job is the same but involves a sequence of short-term contracts, the problems are similar due to the dis-incentives produced by the lack of commitment between the parties.

To define bad jobs, we construct a utility index for each individual and each period, which reflects the employment quality. The index consists of the ratio between labour earnings and the square root of the number of contracts (a standard Cobb-Douglas function that depends positively on income and negatively on rotation). A job is identified as *bad* in terms of the distribution of those utility indices in the population of workers. Following the conventional analysis of poverty measurement (e.g., Chakravarty 2009; Villar 2017), we define bad jobs as those that yield a utility index below 60% of the median of the distribution of utilities in a given reference period. Let us point out that relying on poverty indices to measure the low quality of jobs is a natural strategy which can be found in other studies that measure the degree of precariousness of the labour market. See Gradín et al. (2012), García Pérez et al. (2017, 2020) and the references provided therein.

Using this approach and the aforementioned database, we can identify those workers with bad jobs, follow them along the years, observe how their jobs evolve and examine how likely they are to get stuck into bad jobs. To measure the scar of bad jobs we shall compute the probability of having a bad job five and ten years after entering the labour market, depending on whether the individual had a bad job in the past (at the entrance or in the fifth year). We shall also estimate the scar according to different intensity levels of bad jobs (i.e. whether the degree of job badness affects the likelihood of bad jobs in the future), and analyse the impact of each individual variable (low wages, few hours worked, and high number of contracts). Finally, we compute the evolution of the scar in order to learn the extent to which it is affected by the business cycle, as there is evidence that entering the labour market during a recession has long-term effects on wages (Dolado et al. 2013) and may also affect many other aspects of life (see von Wachter 2020, for a recent survey with international data; and García Pérez and Vall Castelló 2015, García Pérez et al. 2019, for the Spanish case). The estimation involves the usual control variables regarding gender, a proxy for the level of studies, economic sector and region.

Our results show that entering the labour market with a bad job strongly determines having a bad job in the medium term. The observed hysteresis of bad jobs points out the presence of a mechanism that hampers social mobility. Those escaping from bad jobs in the medium term, though, will most likely keep their better jobs in the long run. The intensity of bad jobs is also important, as *high-intensity* bad jobs leave a much deeper scar. The number of hours worked appears as the main driver of the scar, both in the first year relative to the fifth, and in fifth year relative to the tenth. Hourly wages acquire some relevance in the transition from the medium to the long term. Additionally, the business cycle shows a clear influence on the 'depth' of the scar: those in bad jobs during the Great Recession have their future careers marked by a strikingly deeper scar, both in the medium and long term, compared to the pre-crisis cohorts. Finally, we find that bad jobs affect unevenly the different demographic groups, in particular the effect is more severe for women, the less educated young and those entering the hospitality and primary sectors.

The structure of the paper is as follows: Section 2 describes the database, the framework to measure bad jobs, and the strategy to empirically measure the scarring effect of bad jobs. Section 3 provides a descriptive overview of the dynamics of bad jobs in Spain, as well as the evolution of three key dimensions that may affect the quality of jobs in the future. Section 4 presents the estimation results of the scarring effects of bad jobs, explores the role of the business cycle in determining the 'depth' of the scar, and includes a sensitivity analysis. Finally, Section 5 concludes with a summary of our findings and some policy recommendations.

2. Bad jobs: data, definition and measurement

We aim at analysing the influence of entering the Spanish labour market with a bad job on the quality of future employment. The quality of the job is linked to three key variables whose information is provided in our reference database for each year in the relevant time span. Those variables are: hourly wages, number of hours worked, and the number of contracts. We assume that a job is of higher quality (hence "better"), the higher earnings and the higher stability. In the same vein, a job is of "worse" quality (bad job) if it does not provide sufficient income or stability (we discuss below what "sufficient" means).

2.1. Data

The main data source for the empirical analysis is the last wave of the Spanish Continuous Sample of Work Histories (*Muestra Continua de Vidas Laborales*, MCVL, 2019). This microeconomic database provides rich information on a representative sample that involves about 4% of the total individuals affiliated to the Spanish Social Security. This dataset includes information on the full history of every selected individual. It provides detailed information on every affiliation episode to the Social Security, which includes the monthly salary earned[1] and the proportion of a full-time working day actually worked. Based on that information, we can infer the number of contracts signed in a given time-period; the number of hours worked and, subsequently, the average hourly wage.

We focus on the population aged between 16 and 30 who entered the job market from 1997 onwards. Since the last data wave corresponds to 2019, we shall study the dynamics of new entrants between 1997 and 2013 to measure their scar five years later, and between 1997 and 2008 for the analysis of the scar ten years later. We denote by t the year in which individuals enter the job market. To minimize the impact of the different moments of entry along the first year (i.e. to avoid any potential noise underpinning the entry moment, such as working episodes unrelated with future jobs), we take as our first period that corresponding to $t + 1$, which we will refer to as "the first year", even though it is actually the first year after entering the job market. Those people are then revisited in $t + 5$ and $t + 10$, to check how their situation has evolved and, in particular, whether they keep holding bad jobs when they entered the market with one.

The database includes information on salaried workers who have been employed for at least one day during the natural year. Unemployment episodes arising within this period are indirectly reflected in the number of hours worked, which will forcefully be below the maximum allowed for the year. No data are selected regarding young individuals who have been self-employed at any point in time throughout those ten years.

Appendix A provides further details on the description of our database (i.e., individuals aged 16-30 who enter the labour market between 1997 and 2013) and, in particular, on the control variables (gender, age of entry, economic sector, region). Overall, the distribution by gender is relatively even (49% female). Regarding the age of entry in the labour market, we observe that 1 in every 3 workers belongs to the 19-21 age group. The age of entry is to be regarded as a proxy of the education level, given that the database does not provide sufficiently updated information

[1] The salary earned is retrieved from the contribution base, which implies that an upper bound is applicable. However, this upper bound does not affect our analysis since we focus on low wages.

on individuals' educational attainments. One would expect that starting at an older age (to be interpreted as with a higher education level) will reduce the probability of ending up in a bad job. The economic sectors exhibit a rather stable composition.[2] Trade is the largest sector, employing about 20% of the people in our database, followed by industry, hospitality and, to a lesser extent, health and education. Given the divergences in the skills required for the different sectors, as well as the labour market imbalances in others, we expect bad jobs to hit harder sectors such as the hospitality sector. Regarding the region, we take as the proper reference the province of first affiliation to the Social Security.

2.2. Definition of bad jobs

In order to define bad jobs, we now introduce a measure of the quality of the job that can be regarded as a sort of utility index. To be precise, consider a society S in a period t and associate, to each individual $i \in S$, a Cobb-Douglas utility index that depends positively on labour earnings (the product of the hourly wage, $w_i(t)$, and the number of hours worked within the period, $h_i(t)$), and negatively on the number of contracts signed, $c_i(t)$. This utility index is given by:

$$u_i(.) = \frac{w_i(t) \times h_i(t)}{\sqrt[2]{c_i(t)}} \qquad [1]$$

That is, $u_i(.)$ Is the ratio between labour earnings and the square root of the number of contracts, for the corresponding period. Those utility indices describe, in an elementary way, the negative effect of the number of contracts for a given labour income and will serve the purpose of identifying the individuals with bad jobs. Note that utility is linear in income and concave in the number of contracts; moreover, rotation has one half of the weight of each the other two variables (wages and hours worked).[3]

In order to define a bad job, we select a reference utility threshold, q_0, to be understood as the minimal utility required for a job to be considered not-bad (see below). We then define a ***bad job***

[2] For those individuals with contracts in different sectors in a given period (i.e., $t + 1$, $t + 5$ or $t + 10$), we select the sector where they spent the longest period of time.
[3] We discuss an alternative specification of this index in Section 4 and Appendix D.

at time t as one that yields a utility level below such a threshold. Formally, if we call $B(S, t)$ the set of workers with bad jobs in society S at time t, we shall have:

$$i \in B(S,t) \Leftrightarrow u_i(.) < q_0$$

All comparisons will be anchored to this reference value q_0, measuring wages in real terms (constant euros).

Once the utility equation is defined, the key question now is how to set the threshold q_0. As we lack a universal definition to measure the *badness* of jobs—in parallel to the poverty literature—we need a benchmark to compare each worker's situation. To determine the threshold, we select a reference year, and then apply the conventional wisdom in poverty measurement by taking the cut-off given by the 60% of the median of the distribution of the utility index, among *all* employed workers in that year. We focus on the working population in 2007 as the reference point, just before the economic crisis hit.[4] Selecting the overall working population allows one to keep track of the quality of the jobs of the new entrants relative to the whole set of workers at a certain point in time. Summing up, we define a ***bad job*** at time t as one that yields a utility level below the threshold given by the 60% of the median of the distribution of utilities in 2007 for all employed Spanish workers. This approach can thus be regarded as identifying bad jobs with those held by "workers with poor employment", so to speak.

Applying Equation [1] to the utility indices of 2007, we find that the value of the threshold, in constant euros of 2015, is given by: $q_0 = 8{,}635.5$.

This approach also permits one to consider different *intensity levels* of bad jobs, which may help clarifying the impact of entering the labour market with a bad job on the quality of future employment. We shall refer to those levels of intensity, from better to worse, as *low, medium and high* (which could also be understood as *slightly* bad, *fairly bad* and *very* bad jobs, respectively), relative to the median of the overall distribution of the utility index in 2007. In particular, a bad

[4] We provide a sensitivity analysis in Section 4.3 and Appendix D with a different reference year to check the robustness of our results.

job is considered of high, medium or low intensity when the corresponding utility index is below 30%, between 30% and 40%, and between 40% and 60% of that median, respectively.

2.3. Measurement of the scarring effect of bad jobs

The scarring effect of bad jobs, or the hysteresis of bad jobs, refers to the situation in which a bad job in the present may induce a bad job in the future. To measure this potential scar, we estimate several models that involve two dependent variables, different sets of explanatory variables, and some common control variables. Equation [2] summarizes the estimation approach. As already mentioned, the probit models gauge the probability of being in a bad job (B) either in $t+5$ or in $t+10$ after starting the first employment.

$$B_{t+h} = \beta_{0h} + \beta_{1h} * Z^{s}_{t+h} + \beta_{2h} * X + e^{s}_{t+h} \qquad [2]$$

The two dependent variables are the probability of having a bad job in the medium and in the long term (h = 5 and h = 10, respectively). For each of those dependent variables we consider three alternative models, s = 1, 2, 3, that differ with respect to the set Z of key explanatory variables. Additionally, all estimations incorporate a set of additional covariates, X.

In Model 1, bad jobs in $t+5$ or $t+10$ are regarded as a function of their past values and the set of X control variables exclusively. That is, Z refers to the quality employment index in the previous periods. Model 2 uses as explanatory variables (Z) the past values of the intensity of bad jobs, broken down into three levels (high, medium and low intensity). Finally, Model 3 takes as explanatory variables (Z) the separate components of the utility index (hourly wages, hours worked, and number of contracts), divided into four different categories each. In particular: (a) We define four hourly wage categories according to the quartile distribution of the whole employed population in 2007; (b) The number of hours worked (expressed in terms of full-time equivalent months) is divided into the following levels: working less than three months, between three and six months, between six and eleven and more than eleven months in the year; and (c)

The number of contracts signed are broken down in the categories of four or more contracts, three contracts, two contracts, or a single contract (i.e., from higher to lower rotation).

Additional covariates (X) include gender, age group at entry, region of first affiliation, sector of activity (lagged to the previous period), and unemployment rate at entry (see Appendix A for details).[5] As shown by Von Watcher (2020), the unemployment rates at entry might play an important role for young entrants, who can suffer an earnings penalty of the order of 10-15 percentage points when they enter in periods of recession.

Let us point out that there is a number of individuals in the database that appear at time $t + 1$ and then leave the labour market and disappear (either at $t + 5$ or at $t + 10$). The probability of leaving the labour market seems to be linked to the quality of the job, that is, those entering the labour market with worse jobs exhibit higher chances of disappearing from the database (e.g., becoming non-employed for the full 365-day period considered in $t + 5$ and/or $t + 10$). See Figure 2 below. The non-random nature of those individuals who leave the labour market may induce selection bias that can be overcome by recurring to the Heckman two-step procedure (Heckman 1979). In the first step, we calculate the probability of being in the database (i.e., not exiting the labour market). A key consideration in running this procedure is the identification of a variable that affects the selection procedure but does not directly affect the outcome variable, except through selection. The identification variable used is the national rate of unemployment in the immediately preceding year, which affects the likelihood of being in the labour market but does not directly determine that an individual be in a bad job. The selection equation, hence, includes the same control variables as the outcome equation, but it adds the previous year's rate of unemployment.

After estimating those equations, a separate analysis is undertaken in order to study whether the scar varies per year of entry. That is, we investigate whether entering in a bad job at a certain moment in the cycle changes the 'depth' of the scar (in particular, whether entering the job market

[5] Four groups of age at entry are selected: 16-18; 19-21; 22-24; and 25+ (reference). All the Spanish regions are considered (Madrid being the reference). Eight sectors are included: agri-fishing, industry (reference), construction, trade, hospitality, education, health, and other (mainly professional or scientific activities).

with a bad job in a recession increases its negative impact on the future). In this case, we run a probit model (naturally excluding the unemployment rate variable).[6]

3. Bad jobs in the Spanish labour market: overview

This section describes the dynamics of bad jobs in $t+1$, $t+5$ and $t+10$ for the different entry years considered (1997-2013). We have adopted the convention of letting the numbers in the horizontal axis of the figures to denote the entry year in all cases. Take for instance Figure 1 and consider the year 1997. The line $t+1$ at this point tells us the share of people with bad jobs one year after (i.e., in 1998). The line $t+5$ ($t+10$) at that point tells us the share of workers with bad jobs who entered the labour market five years (ten years) earlier, that is, how things were in 2002 (2007).

Figure 1 shows that most of the workers enter the labour market with a bab job. This is clearly indicative of the extent of precariousness of the Spanish labour market for new entrants. Between 1997 and 2004 the share of workers starting their career in bad jobs decreased from 65% to roughly 60%, in an economically booming period. The trend reverted to a steady increase with the financial crisis, with people in bad jobs amounting to 3 out of 4 of the total new jobs considered. This already points out the effect of the cycle on the quality of the jobs, an effect that can still be observed in the medium term ($t+5$): with the crisis, the share jumped up to 51%, to decrease to 38% following the economic recovery. Ten years later, the data convey a similar message, though the share of bad jobs slightly decreases in the latest period for which data are available.

[6] For the sake of conciseness, we only develop the first model when analysing the cycle effect.

Figure 1 Bad jobs as a share of the total employed people (%)

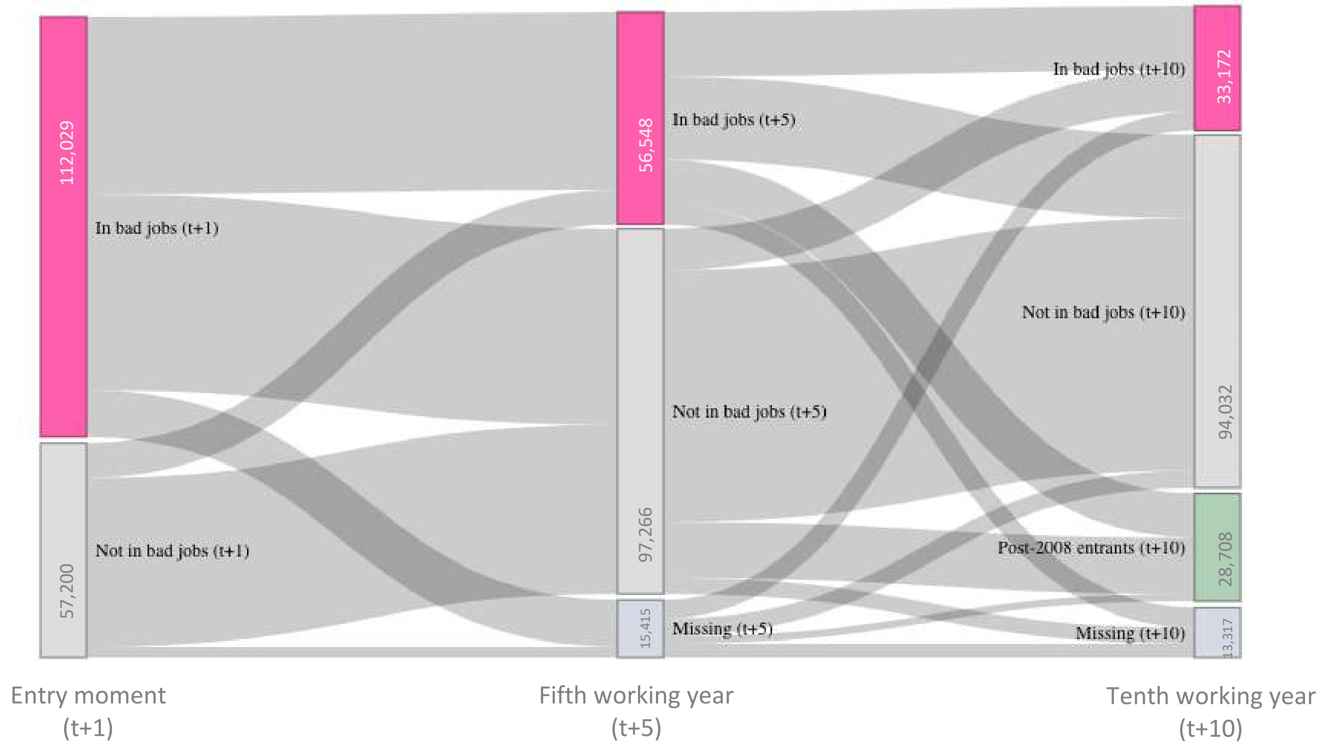
Source: MCVL, authors' own work.

Figure 2 is a flow chart that describes the evolution of the quality of the jobs for the full set of individuals entering the labour market between 1997 and 2013, comparing the situation in the first, fifth and tenth working years. This provides a first indication on the extent of the "scar", which captures how a bad job at present marks the youth for future jobs. Between the first and the fifth working year, 47% of individuals who started with bad jobs moved outside this category. Yet, 43% of them continued holding bad jobs five years later. This contrasts with the fact that only 16% of those who did not start with a bad job ended up with a bad job in $t + 5$. This is a strong indication that the quality of a job when entering the labour market affects the situation in the medium term.

Turning to the longer term, we observe that about one third of the workers with bad jobs in $t + 5$ continued with bad jobs in $t + 10$, whereas only 16% of those not in bad jobs in $t + 5$ transit to bad jobs in $t + 10$ (exactly the same proportion as those transiting from not-bad jobs to bad ones between $t + 1$ and $t + 5$). Such dynamics evidences the presence of a scar generated by the involvement in bad jobs, particularly strong in the longer term. Those who exit bad jobs after five working years have much better prospects of escaping from bad jobs in the long run.

The flow chart also shows that some individuals in the database go astray in $t + 5$ or $t + 10$. Most of those missing observations correspond to people who were in bad jobs in the past, which suggests that some of the individuals with bad jobs are expelled from the labour market. This potential selection bias will be taken into account in the empirical analysis, as already mentioned.

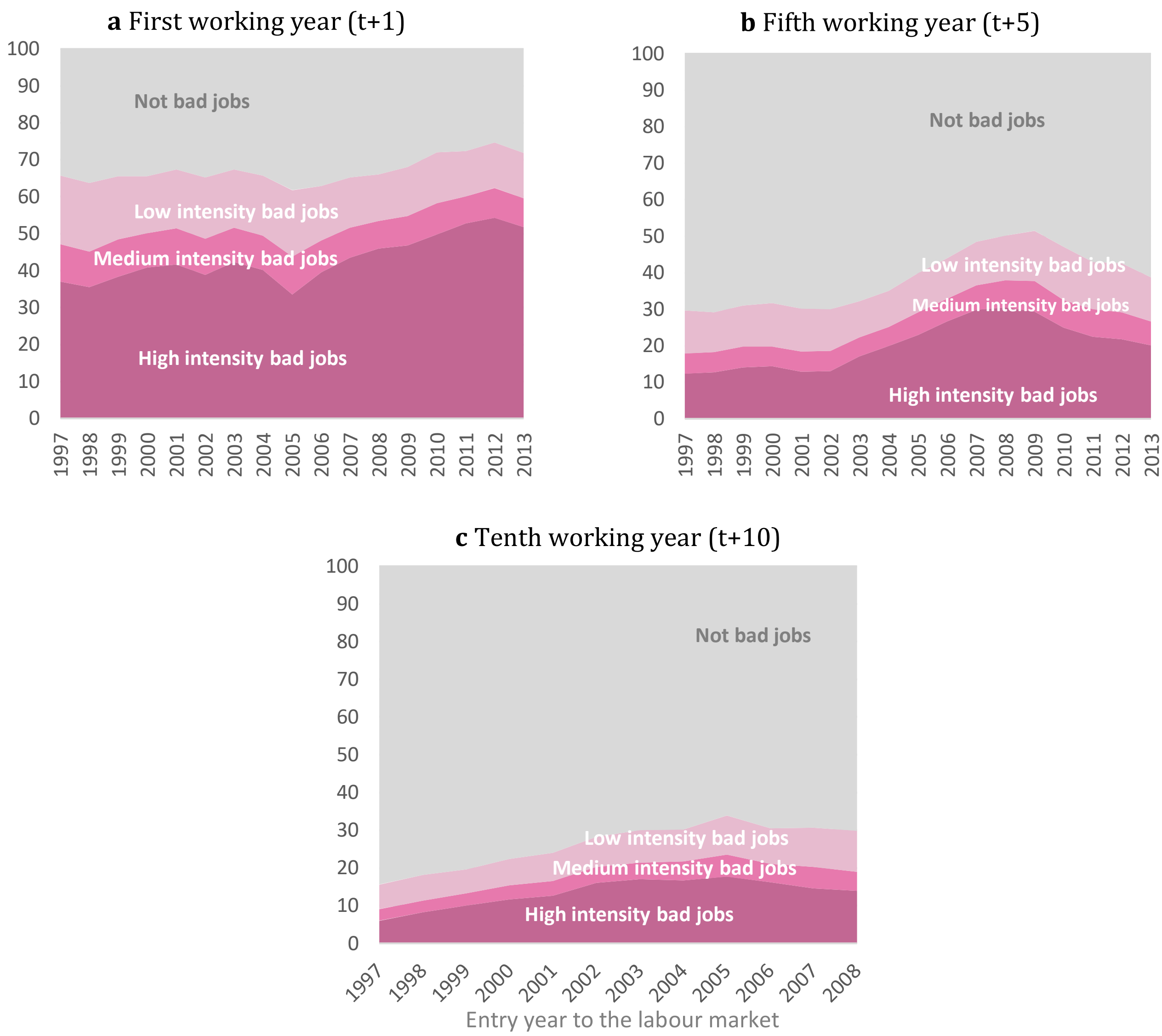
Figure 2 The dynamics of bad jobs in Spain for job entrants in the period 1997-2013



Source: MCVL, authors' own work.
Note: The data refer to job market entrants aged 16-30 for the period 1997-2013. Post-2008 entrants are included in a separate category in t+10 given the lack of data availability for this cohort and later ones, since the last available year in the database is end-2019.

Figure 3 provides new insights on the dynamics of bad jobs by dividing them by intensity levels (high medium or low intensity). It shows that most of the bad jobs are of high intensity in all points in time.

Figure 3 Share of bad jobs by intensity over time (%)



Source: MCVL, authors' own work.
Note: Job categories are defined according to Equation [1]. Low intensity bad jobs comprise those between 40% and 60% of the median; medium intensity bad jobs refer to those in the 30-40% range; and high intensity bad jobs refer to those below 30% of the median. For the fifth and tenth working years, we exclude the people who no longer are in the labour market (included in the "missing" category in Figure 2). In the tenth year, we also exclude the post-2008 entrants given lack of data availability.

Figure 4 shows the composition of the new entrants in the labour market at $t+1$, $t+5$ and $t+10$, by levels of the corresponding variable (hourly wages, hours worked and contracts signed). As intuition suggests, workers' conditions improve in all dimensions as they gain experience.

Panel A shows the share of workers in each hourly wage category. Focusing on the first year of entry, we observe that the share of those starting with very low wages diminished steadily between 1997 and 2006. The Great Recession altered that pattern as the share of young workers with lower wages increased to reach 45% of the total in 2012. Looking at the situation five years later we observe a similar trend—reflecting the cycle effect—though the share of workers on jobs with very low hourly wages decreases significantly as compared to that of the entry year. The peak of very badly-paid jobs after five years of work corresponds to those entering the job market during the Great Recession in 2008 (i.e., when analysing year 2013).[7] Both the entry year and the fifth working year show a marked counter-cyclical trend, which practically vanishes in the long term, also given the lack of data for the post-2008 generation. The change observed between the fifth and the tenth year is much smaller and the effect of the economic cycle is softer.

Regarding the number of hours worded, Panel B shows that a large share of entrants work very few hours (the equivalent to less than three months full time). This trend was not reverted even throughout the booming years. Complementarily, the share of new entrants working at least eleven months seems to shrink along the years. The share of young people working few hours in $t+5$ diminishes significantly with respect to $t+1$. The crisis gets its toll, however, and we observe that the share of workers with low hours raised. In the longer term, the share of people working very few hours increases for entrants up to 2003 (i.e. those entrants who, in the longer term, are working during the recession years), to remain constant after that. That is, as the economy recovered, the proportion of people working very few hours did not decrease, which clearly indicates that the recovery after the crisis was far from complete regarding the labour market (in particular, due to the presence of unemployment episodes and the increase of temporary contracts).

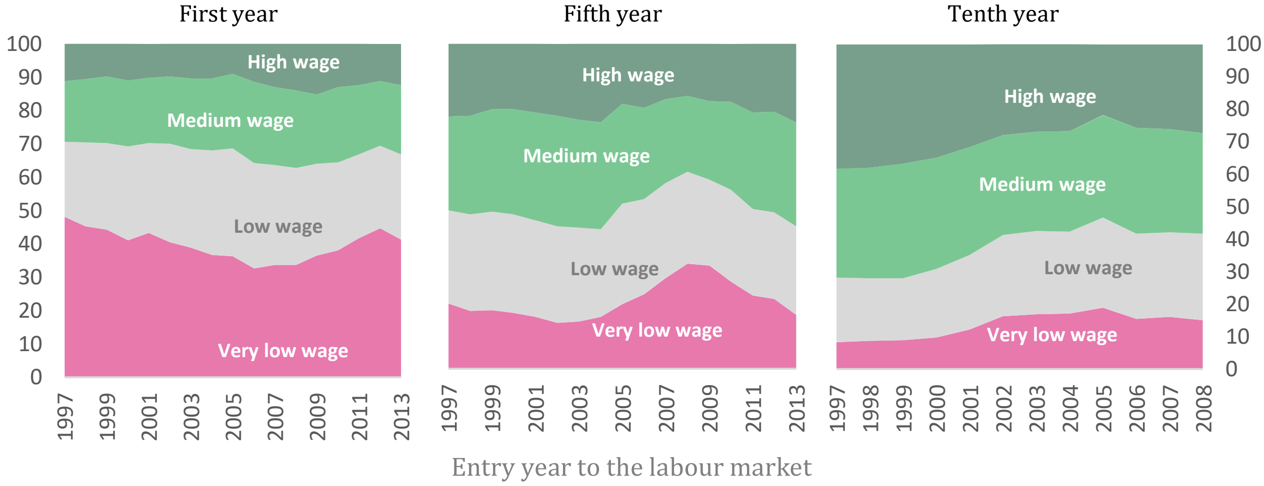
Panel C shows that over 70% of the workers have 1 or 2 contracts per year. While workers with just one contract per year make up the largest share of all categories, a decreasing trend is observed when analysing the medium and longer term. The crisis triggered a fall in single-contract working episodes, to the detriment of those involving three or more contracts. It should be noted,

[7] After that, this share decreases, which may be partly be the result of collective bargain agreements as well as the subsequent labour reforms undertaken since 2012.

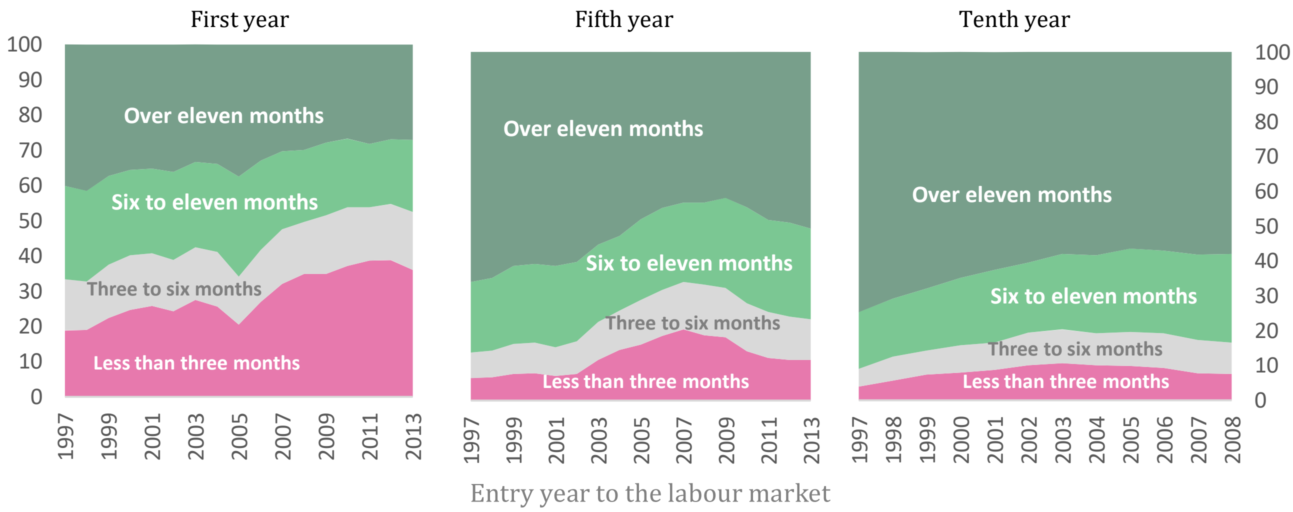
however, that—taken in isolation—the number of contracts does not provide information about its duration (i.e. a single contract might last a day or a full year), which implies that this indicator has limited explanatory value on its own.[8]

Figure 4 Share of workers by category of wages, hours and contracts by entry year (cut-off of entrants in 2008 at period $t + 10$)

a Wage per hour

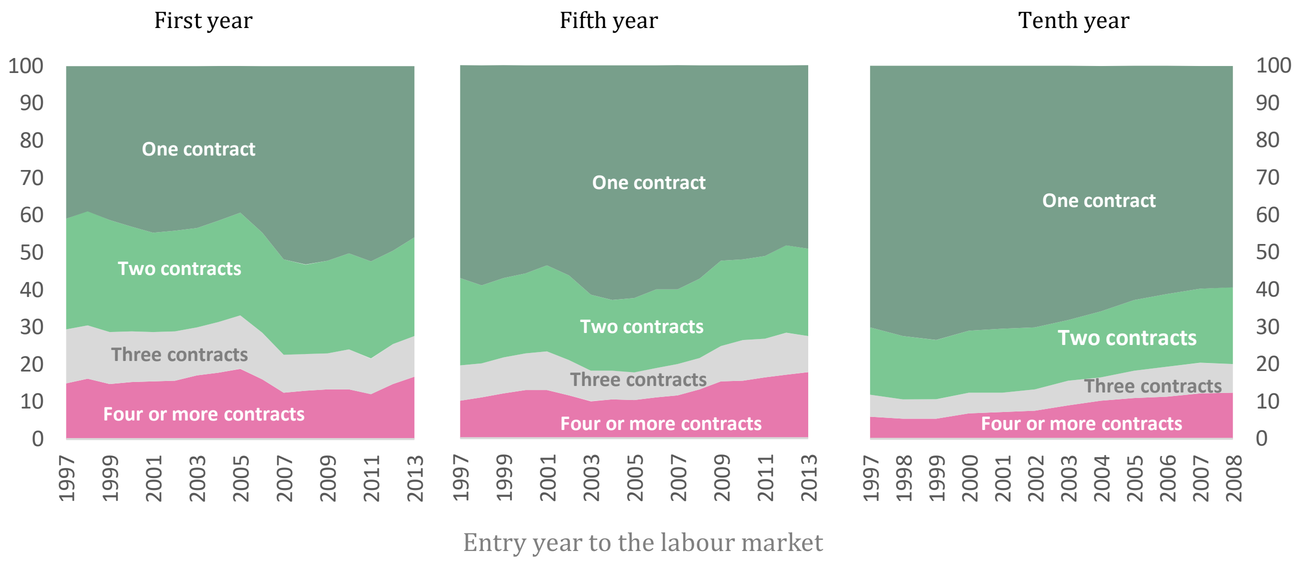


b Hours worked (equivalent in months worked full time)



[8] In fact, the correlation between hours and contracts is very weak (a coefficient of 0.116 for t+1, 0.259 for t+5 and 0.302 for t+10).

c Number of contracts



Note: For hours worked and wage per hour, the lower group does include the referenced category; the second and third groups include the upper referenced category; and the highest group does not include the referenced category. The brackets for hourly wage are determined by the wage distribution of the employed population in 2007. The quartiles are defined by the following thresholds (in constant euros of 2015): 6.74, 8.71 and 12.76.

4. The scarring effects of bad jobs

4.1. Main results

We now present the estimates of the marginal probabilities of having a bad job five and ten years after entering the job market (models A and B, respectively), controlling for certain characteristics of the workers (age, gender, economic sector, region and unemployment rate). For each of the two points in time, we provide three complementary estimates as detailed in Section 2. The first refers to the scarring effect of having a bad job in the past. The second uses the intensity of bad jobs as explanatory variables, to examine whether the 'depth' of the scar varies depending on how bad the past job was. The third aims to identify the relative importance of the three key dimensions that might influence the future quality of jobs: wages, hours worked and number of contracts—each broken down into four levels.

Table 1 offers the estimation results for these three models when the dependent variable is having a bad job in $t + 5$. Model 1A clearly shows that having a bad job at entry has a strong effect on having a bad job five years later. In particular, it increases the probability of continuing in a bad job in the medium term by 21.8 percentage points. Compared to the predicted probability of being in a bad job in the medium term for workers who did not start in a bad job (17.9%), starting in a bad job would more than double the probability of being in a bad job in the medium term (almost 40%). Other covariates, such as age of entry or economic sector, are also significant but with smaller impact (see Appendix B for details). In particular, entering at an early age increases the probability of having a bad job five years later; this is due to the fact that those new entrants are the youngest and hence those with lower levels of study. Entering the labour market in the hospitality or the agri-fishing sectors also increases the likelihood of ending up in bad job five years later.

Model 2A reveals the importance of the intensity of bad jobs. Those starting with a high-intensity bad job are much more likely to continue in a bad one in the medium term, relative to the other categories (medium and low intensity).

Model 3A shows that the number of hours worked during the entry year is the most significant variable in magnitude, the one that leaves the deepest scar. In particular, those working very few hours—no more than three months full time—have about 28 percentage points higher probability of having bad jobs in the medium term, when compared to those over eleven months full time throughout the whole starting year. For the second lowest group of hours worked—working between three and six months in equivalent full time—the scar decreases slightly to some 21 percentage points. Lastly, those working the equivalent to six-to-eleven months full time exhibit a substantially lower scar (14 percentage points). The scar induced by the initial hourly wage is substantially lower. Those in the two lowest quartiles have a 10 and 14 percentage point probability higher of incurring bad jobs in the medium term, respectively, compared with the top quartile. Moreover, the scar associated with initiating the career in the third quartile of hourly wages is practically negligible. Lastly, job rotation seems to play a much lesser role in determining the probability of being in a bad job five years later, even though the scar diminishes when the number of contracts shrinks. Yet the informative content of this variable alone is limited, as already mentioned.

Table 1 Estimation results: bad jobs in the medium term (t+5), marginal probability

	Model 1A	**Model 2A**	**Model 3A**
Bad job (t+1)	0.218***		
	(0.002)		
Low intensity bad job (t+1)		0.149***	
		(0.004)	
Medium intensity bad job (t+1)		0.203***	
		(0.004)	
High intensity bad job (t+1)		0.274***	
		(0.003)	
Wage very low (t+1)			0.141***
			(0.004)
Wage low (t+1)			0.104***
			(0.004)
Wage medium (t+1)			0.0500***
			(0.005)
Hours <3 months (t+1)			0.277***
			(0.003)
Hours 3-6 months (t+1)			0.214***
			(0.004)
Hours 6-11 months (t+1)			0.135***
			(0.003)
Contracts 4+ (t+1)			0.0556***
			(0.003)
Contracts 3 (t+1)			0.0220***
			(0.004)
Contracts 2 (t+1)			0.0122***
			(0.003)
Observations	161,395	161,395	161,395
Predicted probability of bad jobs in t+5 for the reference group [1]	0.1793762	0.1760365	0.1127347

Note: standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1. The model also controls for age at entry, sector at entry, region of first affiliation and the unemployment rate at entry. The reference categories are as follows: age group 25+, industry sector, and the region of Madrid; highest hourly wage group (fourth quartile); highest working hours group (equivalent to eleven or more months worked full time); and lowest rotation group (just one contract in the analysed period). More detail is available in Appendix B. [1] The reference group in Model 1A and 2A refers to individuals who were not in bad jobs in t+1; in Model 3A, to individuals who were in the top groups of the three considered dimensions (i.e., top hourly wage quartile, working full-time for the whole year, and single contract signed) in t+1.

Table 2 presents the scarring effect of bad jobs over the long term ($t + 10$). Model 1B shows that the scar left by bad jobs in the medium term is the key determinant of bad jobs in the long term. That is, the medium-term scar dominates the initial one, suggesting that those who are able to *escape* bad jobs in the medium term will most likely not be in bad jobs in the long term. On the contrary, those holding bad jobs in the fifth year have a significantly higher likelihood of keeping them in the long term.

Specifically, the predicted probability of having a bad job in the long term would be: (1) equal to 17.5% if the individual did not start in a bad job, and close to 24% for those who did start in a bad job; and (2) equal to 14% if the individual was not in a bad job in $t + 5$, and approximately 36% if that individual was in a bad job in that period (yielding an estimated scar of 22.1 percentage points).

Model 2B provides a similar message in terms of the importance of the medium-term situation. The worse the overall quality of jobs in the medium term, the higher the likelihood to continue in bad jobs in $t + 10$. In particular, those with high intensity bad jobs over the medium term have a 27.5 percentage points higher likelihood of continuing in a bad job than those who were not in such a situation. The equivalent number for people in medium intensity and low intensity bad jobs is 23.6 and 17.2 percentage points, respectively. This contrasts to the much lower scar marked by the initial situation, which does not surpass an estimated magnitude of 8.6 percentage points.

Analysing separately the three key dimensions related to the quality of jobs, we find, again, that working few hours five years after entering the labour market has a strong effect on the quality of the job in the long term (Model 3B). Conversely, the initial situation does not provide such a scar, either as regards hours or the other two components (wages and contracts). Bad jobs in terms of low wages in the medium term do affect the likelihood of bad jobs in the long term, but to a lesser extent than working few hours. In any case, low wages become more relevant to determine the long-term situation than they did in the medium term. Finally, having more than three contracts within the fifth working year does not entail a large scar over the long term.

With respect to the other control variables, our conclusions are similar to those regarding the medium-term analysis. Namely: (i) the younger the workers enter the labour market, the higher the likelihood of ending up in bad jobs in the long term; (ii) female workers are more likely to be involved in bad jobs; (iii) working in the construction and hospitality sectors in the medium term involves a higher likelihood of being in a bad job in the long term, as opposed to industry or education, both being the sectors with the lowest likelihood of bad jobs.

Table 2 Estimation results: bad jobs in the long term (t+10), marginal probability

	Model 1B	**Model 2B**	**Model 3B**
Bad job, overall (t+1)	0.0640***		
	(0.003)		
Bad job, overall (t+5)	0.221***		
	(0.005)		
Low-intensity bad job (t+1)		0.0685***	
		(0.004)	
Medium-intensity bad job (t+1)		0.0861***	
		(0.005)	
High-intensity bad job (t+1)		0.0585***	
		(0.003)	
Low-intensity bad job (t+5)		0.172***	
		(0.005)	
Medium-intensity bad job (t+5)		0.236***	
		(0.007)	
High-intensity bad job (t+5)		0.275***	
		(0.007)	
Wage very low (t+1)			0.0660***
			(0.005)
Wage low (t+1)			0.0488***
			(0.005)
Wage medium (t+1)			0.0238***
			(0.005)
Hours <3 months (t+1)			0.0136***
			(0.003)
Hours 3-6 months (t+1)			0.0423***
			(0.004)
Hours 6-11 months (t+1)			0.0288***
			(0.003)
Contracts 4+ (t+1)			0.0262***
			(0.004)
Contracts 3 (t+1)			0.0216***
			(0.004)
Contracts 2 (t+1)			0.00717*
			(0.003)
Wage very low (t+5)			0.231***
			(0.006)
Wage low (t+5)			0.161***
			(0.005)
Wage medium (t+5)			0.0972***
			(0.004)
Hours <3 months (t+5)			0.277***
			(0.007)
Hours 3-6 months (t+5)			0.222***
			(0.006)
Hours 6-11 months (t+5)			0.118***
			(0.004)
Contracts 4+ (t+5)			0.0730***
			(0.004)
Contracts 3 (t+5)			0.0421***
			(0.004)
Contracts 2 (t+5)			0.0289***
			(0.003)
Observations	125,215	125,215	125,215

	Model 1B	Model 2B	Model 3B
Predicted probability of bad jobs in t+10 for the reference group (t+1) [1]	0.1852735	0.1882533	0.1694997
Predicted probability of bad jobs in t+10 for the reference group (t+5) [1]	0.1464319	0.1459157	0.0704166

Note: standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1. The model also controls for the region of first affiliation and the unemployment rate at entry. The reference categories are as follows: age group 25+, industry sector, and the region of Madrid (regional variables not shown); highest hourly wage group (fourth quartile); highest working hours group (equivalent to eleven or more months worked full time); and lowest rotation group (just one contract in the analysed period). Full estimation results available upon request. Post-2008 entrants are not regarded in this model, as it is lack of data availability, in first instance, rather than selection bias what explains these cohorts not being included in the database. More detail is available in Appendix B. [1] The reference group in Model 1B and 2B refers to individuals who were not in bad jobs in t+1 or in t+5, respectively; in Model 3B, to individuals who were in the top groups of the three considered dimensions (i.e., top hourly wage quartile, working full-time for the whole year, and single contract signed) in t+1 and t+5, respectively.

4.2. The impact of the economic cycle

We now estimate the probability of having a bad job in $t + 5$ and $t + 10$, using the past values of bad jobs as the explanatory variables, separately for each generation of job market entrants (i.e., Models 1A and 1B adapted to their annual nature).[9] We do so in order to infer to what extent the scar varies depending on the cycle, by focusing on the entry year. For the sake of simplicity in exposition, we concentrate on the simpler models that reflect whether the individuals incurred bad jobs in the past (i.e., when $s = 1$ in Equation [2]).

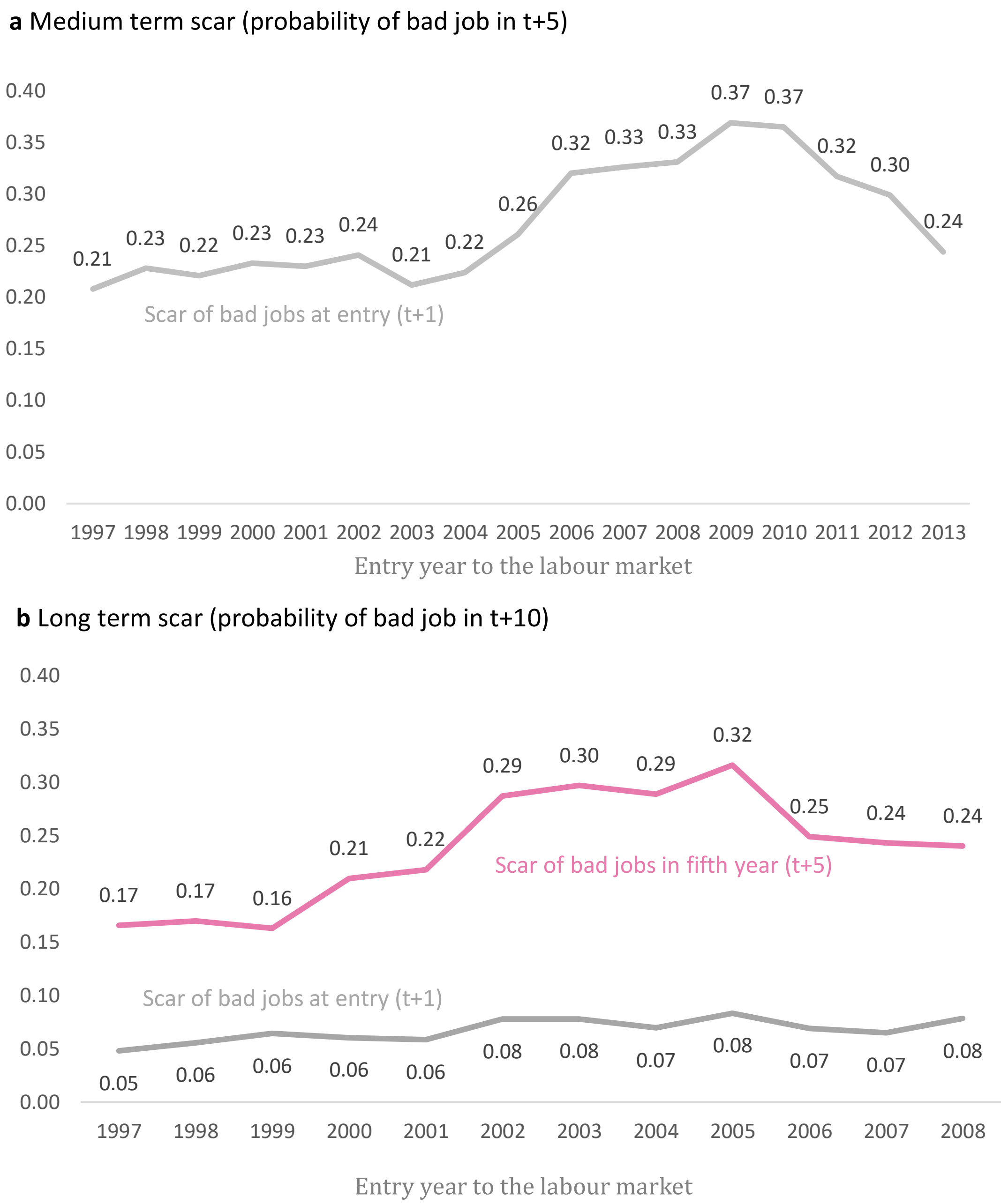
Figure 5 shows the scar estimated for each entry year (Appendix C shows the estimation results in more detail, as well as the underlying predicted probabilities). The first panel shows the scar marked by the entry job in terms of the probability of continuing in a bad job over the medium term. A cyclical trend clearly emerges: those starting with bad jobs during the crisis have a strikingly higher scar as compared to the pre-crisis cohorts. As an illustration, the generation of 2008 that did not start with a bad job has a predicted probability of being in one such job in the medium term of 28.2%. Conversely, if the worker started in a bad job, the chances more than double, amounting to a startling 61.3% (a scar of 33.1 percentage points). Moreover, as the crisis developed, so did the 'depth' of the scar: those starting in bad jobs over those years, and

[9] In this case, we run a simple probit model. We do not opt for the Heckman two-step procedure because the lagged unemployment rate previously used in the selection model is not compatible with the annual nature of the models included in this section.

particularly those in 2009-2010 have more than 36 percentage points higher probability of continuing in a bad job in the medium term as compared to those who did not start in bad jobs. For instance, the cohort of 2010 who did not start in bad jobs has a 20.1% chance of incurring one five years later, as opposed to those starting in bad jobs, whose likelihood of continuing in bad jobs over the medium term amounts to 56.6% (a scar of 36.5 percentage points). This compares to the minimum scar estimated, which corresponds to those working in 1998 (and, hence, entering in 1997) and amounts to 20.1 percentage points.

Turning to the longer term, the scar left by starting with a bad job is relatively constant over time and the magnitude is significantly lower than the medium-term scar, as was also observed in the previous section. The medium-term scar, however, exhibits a cyclical behaviour. The starting point of the chart corresponds to the 1997 cohort working throughout year 2002. It is evident that those with five years' experience working in bad jobs between 2004 and 2010 have an increasingly higher scar that marks their likelihood of having bad jobs in the future. The following year, the trend decreased, to stabilise up until the point where data is available. To place the scar into context, the following example compares the probability of being in bad jobs in the longer term depending on the situation in the medium term. Taking the cohort of 2008 not involved in bad jobs in $t+5$, we find that they have a 14.3% likelihood of being in bad jobs in t+10. In contrast, the same cohort involved in bad jobs in $t+5$ has a 38.3% probability of being involved in one such job in the long term, yielding the estimated scar of 24 percentage points.

Figure 5 The scarring effect of bad jobs over the medium and long term by entry year into the labour market



Source: MCVL, authors' own workings.

4.3. Sensitivity analysis

Relying on a database that permits one to follow the status of the workers along the years, we have defined bad jobs as those that exhibit a quality index below the 60% of the median of the overall distribution in a reference year. Such a quality index combines three key variables that determine the workers' utility: hourly wages, number of hours worked, and rotation. From this, it follows that the choice of the quality index and the reference year may affect the outcomes of our study, so that it is interesting to carry out a sensitivity analysis on those elements.

Redefining the utility equation

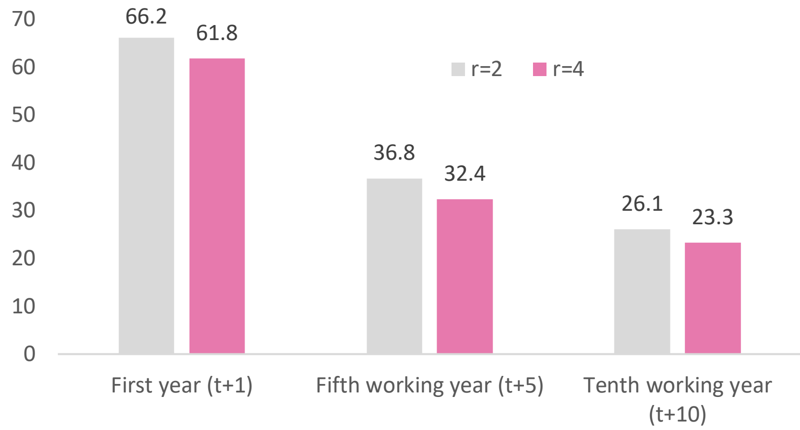
Let us discuss first the role of the utility index and how the particular formula may affect the outcomes. We have defined bad jobs in terms of the distribution of a utility index that is a function increasing and linear in labour income and decreasing and concave in rotation. Equation [1] can be regarded as a particular case of the uniparametric family of functions:

$$u_i^r(.) = \frac{w_i(t) \times h_i(t)}{\sqrt[r]{c_i(t)}}$$

Here $r \geq 1$ is the parameter that controls the degree of concavity of the denominator: the larger the value of r, the smaller the negative impact of rotation on the index. When $r = 2$, as in our reference model, if the worker has earned y euros within the period, the index would be equal to y if the worker had a single contract but that would yield a value $y/2$ if the same amount was obtained through 4 different contracts. This $y/2$ value would be achieved by 9 contracts for $r = 3$, 16 for $r = 4$, and so on. It is easy to see that function $u_i^r(.)$ is homogeneous of degree $\frac{2r-1}{r}$. The degree of homogeneity of this family of functions moves, therefore, between 1 (for $r = 1$) and 2 (as $r \to \infty$), so that $r = 2$ yields a degree of homogeneity equal to 1.5, the midpoint between those two extremes.

We now consider how the results would change if we substitute $\sqrt[2]{c_i(t)}$ in the denominator of Equation [1] by $\sqrt[4]{c_i(t)}$ and recalculate the corresponding values (the threshold q_0, the shares of workers with bad jobs and the probabilities of having bad jobs in the medium and long term). The new value of the threshold would be $q_0 = 9{,}108.35$, larger than before, as we have decreased the denominator of the equation. Figure 6 compares the share of people in bad jobs under the utility function on the baseline scenario ($r = 2$) and that defined under the current scenario ($r = 4$). We observe that the share of people with bad jobs decreases, as should be, but only slightly and mostly in the short term.

Figure 6 The share of bad jobs in Spain (%) for job market entrants in 1997-2013 under alternative definitions of the utility function



Source: MCVL, authors' own calculations.

The new estimates for the marginal probabilities for Model 1 are reflected in Table 3 (see Appendix D1 for more details), together with those of the baseline model, keeping the convention of letting A and B denote medium and long term, respectively. The results are very similar to those already presented in Section 4, so that the sensitivity analysis confirms that the choice for $r = 2$ does not seem to bias the analysis.

Table 3 The estimated scar of bad jobs, comparison for the different definitions of the utility index

	Bad job in t+5		**Bad job in t+10**	
	Model 1A' (r=4)	Baseline Model 1A (r=2)	Model 1B' (r=4)	Baseline Model 1B (r=2)
Bad job overall (t+1)	0.203***	0.218***	0.0560***	0.0640***
	(0.002)	(0.002)	(0.003)	(0.00)
Bad job overall (t+5)			0.218***	0.221***
			(0.006)	(0.005)

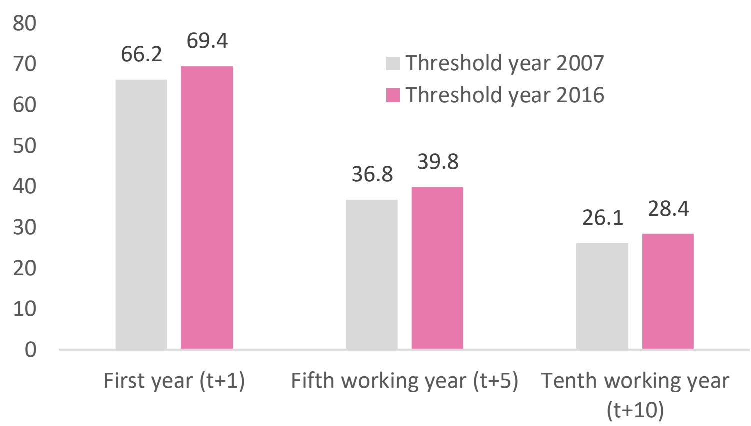
Source: MCVL, authors' own workings.
Note: All models control for gender, age at entry, sector, unemployment rate at entry and region of first affiliation. See more in Appendix D.

The reason why the results are so similar, even though the weight of rotation changes substantially, is because the index is simply used to define the threshold that divides the new entrants in the labour market, whereas the ensuing metric basically correspond to a head-count ratio.

Resetting the reference year

We now provide another sensitivity analysis regarding the role of the choice of 2007 as the reference year for the threshold that defines the bad jobs, by taking 2016 as our new reference year.[10] Making the pertinent calculations, we also observe here that changing the reference year only changes slightly the overall results. The new threshold corresponds to $q_0 = 9{,}459.6$ (about 10% higher than the one obtained for 2007). Figure 7 shows the proportion of people in bad jobs for the two alternative reference years. The share of people in bad jobs is obviously larger taking 2016 as our reference year, but only slightly (about 3 percentage points).

Figure 7 The share of bad jobs in Spain (%) for job market entrants in 1997-2013 under an alternative definition of the threshold (based on year 2016) to define bad jobs



Source: MCVL, authors' own calculations.

Table 4 provides the new estimates of the scar, together with the original ones (Appendix D2 provides further details on the estimation results). We observe that hose estimates are very close to the original ones, both in the medium and the longer term. The maximum difference attained between the two scars does not exceed 2 percentage points. As before, this indicates that the choice of the reference year to set up the threshold that defines bad jobs does not seem to bias the analysis.

[10] To calculate this new threshold, we take the set of individuals employed in 2016 (as per the 2016 wave of the MCVL) and analyse the distribution of the utility function for that society.

Table 4 The estimated scar of bad jobs, comparison for the different threshold years

	Bad job in t+5		Bad job in t+10	
	Model 1A'' (threshold 2016)	Baseline Model 1A (threshold 2007)	Model 1B'' (threshold 2016)	Baseline Model 1B (threshold 2007)
Bad job overall (t+1)	0.234***	0.218***	0.0560***	0.0700***
	(0.002)	(0.002)	(0.003)	(0.003)
Bad job overall (t+5)			0.218***	0.233***
			(0.006)	(0.005)

Source: MCVL, authors' own work.
Note: All models control for gender, age at entry, sector, unemployment rate at entry and region of fist affiliation. See more in Appendix D.

5. Final comments

The quality of the jobs is a topic of increasing concern, particularly in Spain. The recovery from the financial crisis has shown that the substantial reduction of unemployment experienced had some worrying features, especially regarding precariousness and unemployment duration, on the one hand (García Pérez et al. 2020, Gorjón et al. 2020), and the income distribution, on the other hand (Anghel et al. 2018). The economic impact of the Covid-19 on the labour market makes this discussion even more relevant and introduces new elements, such as suspended jobs and discouraged workers (see Von Watcher 2020; García-Pérez and Villar 2020). We have addressed here one particular aspect of this problem, namely, the medium- and long-term incidence of starting the labour career with a bad job. This is a crucial aspect, as it affects the dynamics of income distribution, especially regarding social mobility, through the evolution of labour earnings.

Spain is the European country with higher rate of temporary contracts (above 21% of the total, almost twice the EU-27 average), which are highly concentrated in the younger cohorts. This partly explains the high elasticity of the employment to the cycle and makes hiring and firing workers the main adjustment variable. New entrants are, therefore, subject to high uncertainty regarding the stability of their jobs, and to frequent unemployment spells, which is part of the low quality of their jobs. Moreover, there is a large share of undesired part-time jobs, mostly undertaken by women, and many jobs that have a strong seasonal component (e.g., tourism, agro-fishing activities).

The combination of the institutional setting and the economic structure produces a distributional conflict between generations, and sets a kind of *sorting mechanism* that penalises those who start with worse jobs and do not move away soon enough. Bad jobs become sticky mostly for those working few hours during the initial years, a feature related to gender, lower levels of education and particular economic sectors. The initial distributional conflict between generations, hence, becomes a distributional conflict across economic sectors, gender, and educational levels.

This paper shows that the vast majority of Spanish young workers face a bad job in their first working years. Indeed, most of them start with high-intensity bad jobs. Even though many of them will move towards better jobs few years later, there is a substantial fraction that gets trapped into those bad jobs. Our results show that having a bad job at entry is the main explanation for having a bad job five years later. Moreover, those starting in high-intensity bad jobs exhibit much larger probability of having a bad job in the medium term (a deeper scar). Not surprisingly, the depth of the scar is larger for those who enter the market at an early age, hence with lower levels of education. In addition, we find that the scar is quite sensitive to the economic cycle and that entering the job market in the hospitality or agri-fishing sectors increases the probability of having a bad job five years later, relative to other sectors (both sectors exhibit a strong stational component, which increases rotation, workers with lower levels of education, and a higher share of part-time jobs).

The same pattern repeats when analysing the situation in the long term, but in this case, the medium-term situation—rather than the initial one—is the main determinant of bad jobs after ten years. In other words, those who are able to improve their job situation in the medium term tend to consolidate their better jobs in the long run, whereas those who get trapped in bad jobs in $t + 5$ are much more likely to maintain the situation in $t + 10$.

The analysis also indicates that the number of hours worked is the main determinant of the hysteresis of bad jobs. Hourly wages become more relevant when comparing the medium and the long run. The number of contracts, taken in isolation, does not play a significant role in the probability of holding bad jobs along the years (the reason being, as explained above, that this variable has limited explanatory value when taken in isolation).

Our study provides some insights that might be relevant for policymaking. First and foremost, as already stressed, starting with a bad job can have long-term negative consequences, if this situation is not reverted early enough throughout the working career. It is crucial, hence, to identify those groups who are more likely to stagnate in bad jobs, and to design preventive actions at an early stage. Given that the number of hours worked is the main determinant of the scar, reducing the share of temporary contracts seems to be one of the key measures to avoid consolidating low-quality employment. Complementarily, actions can be taken to improve the performance of public employment services in order to reduce unemployment episodes early in their career. By providing guidance and effective training sessions, this policy would prevent a potentially long-lasting situation of precariousness and would also to assure a more efficient use of public resources.

Second, as the lesser educated young workers present a higher risk of being trapped in bad jobs, efforts to avoid leaving too early the educational system are important for the quality of future employments. The scar of bad jobs is an expression of the role that education (together with family and social networks) plays on the dynamics of income distribution. The educational level is a proxy of people's competencies, which will likely affect the options open to start working and to make progress on the job (most notably, they will impact on the sector and, consequently, the wage, number of hours and type of contract). It should be noted that even though women exhibit higher educational levels than men, they present higher probability of having bad jobs in the future, partly due to the segregation bias among economic sectors.

Finally, it would be wise to think of ways of avoiding the long-term consequences of decisions made at an early stage of the working life, by providing opportunities of permanent updating of knowledge and abilities. This may help revert some of the implications of a bad start even in the long term, especially as the IV industrial revolution gains momentum and menaces many traditional occupations. This can be regarded as a "second chance" policy to prevent that decisions made very early in life, regarding schooling and occupation, condition job opportunities forever. In this way, the policy would enable to reduce the ratchet effect of early-stage decisions, which would inevitably take place even if those decisions were made under perfect equality of opportunity (which is not the case).

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Appendices

Appendix A: Summary statistics of control variables

Table 6 provides the summary statistics of the main control variables that our analysis will focus on. The table presents the information in an aggregate way, including the whole set of workers eligible in the study: entrants aged 16-30 between 1997 and 2013.

Table 6 Summary statistics of the database (entrants aged 16-30 between 1997 and 2013)

	Share over total (%), unless stated		
Female	49.0		
Age at entry 16-18	25.0		
Age at entry 19-21	31.78		
Age at entry 22-24	20.24		
Age at entry 25+	22.98		
	t+1	**t+5**	**t+10**
Agri-fishing	0.6	0.6	0.5
Industry	12.5	13.5	14.7
Construction	9.4	8.8	7.0
Trade	22.1	21.1	20.1
Hospitality	10.8	9.7	8.4
Education	3.8	4.1	4.5
Health	5.8	7.6	8.5
Other	34.9	34.6	36.4
Andalucía	16.2		
Aragón	2.7		
Asturias	2.3		
Baleares	2.3		
Canarias	4.9		
Cantabria	1.4		
Castilla y León	5.2		
Castilla-La Mancha	3.9		
Cataluña	17.0		
Comunidad Valenciana	9.4		
Extremadura	1.8		
Galicia	6.1		
Comunidad de Madrid	17.1		
Murcia	2.7		
Navarra	1.4		
País Vasco	4.9		
La Rioja	0.6		
Ceuta and Melilla	0.3		
Unemployment rate at entry (average)	13.9		

Source: MCVL 2019; and Eurostat.

Appendix B: Detailed estimation results for the medium and long term

Table 7 Detailed estimation results for bad jobs in the medium term (t+5)

	Model 1	Model 2	Model 3
Bad job, overall (t+1)	0.218***		
	(0.002)		
Low-intensity bad (t+1)		0.149***	
		(0.004)	
Medium-intensity bad (t+1)		0.203***	
		(0.004)	
High-intensity bad (t+1)		0.274***	
		(0.003)	
Wage (t+1) very low			0.141***
			(0.004)
Wage low (t+1)			0.104***
			(0.004)
Wage medium (t+1)			0.0500***
			(0.005)
Hours <3 months (t+1)			0.277***
			(0.003)
Hours 3-6 months (t+1)			0.214***
			(0.004)
Hours 6-11 months (t+1)			0.135***
			(0.003)
Contracts 4+ (t+1)			0.0556***
			(0.003)
Contracts 3 (t+1)			0.0220***
			(0.004)
Contracts 2 (t+1)			0.0122***
			(0.003)
Age at entry 16-18	0.145***	0.128***	0.128***
	(0.004)	(0.004)	(0.004)
Age at entry 19-21	0.0724***	0.0600***	0.0521***
	(0.003)	(0.003)	(0.003)
Age at entry 22-24	(0.004)	-0.00802*	-0.0154***
	(0.003)	(0.003)	(0.003)
Unemp. rate at entry	0.00378***	0.00326***	0.00344***
	(0.000)	(0.000)	(0.000)
Female	0.0630***	0.0600***	0.0562***
	(0.002)	(0.002)	(0.002)
Agri-fishing	0.107***	0.0940***	0.0933***
	(0.015)	(0.015)	(0.015)

	Model 1	Model 2	Model 3
Construction	0.0674***	0.0656***	0.0620***
	(0.005)	(0.005)	(0.005)
Trade	0.0233***	0.0163***	0.0105**
	(0.004)	(0.004)	(0.004)
Hospitality	0.131***	0.114***	0.104***
	(0.005)	(0.005)	(0.005)
Education	0.0193**	(0.001)	(0.004)
	(0.007)	(0.006)	(0.006)
Health	0.0263***	0.0162**	0.0274***
	(0.006)	(0.006)	(0.006)
Observations	161,395	161,395	161,395

Note: standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The model also controls for the region of first affiliation and the unemployment rate at entry. The reference categories are as follows: age group 25+, industry sector, and the region of Madrid (regional variables not shown); highest hourly wage group (fourth quartile); highest working hours group (equivalent to eleven or more months worked full time); and lowest rotation group (just one contract in the analysed period). Full estimation results available upon request.

Table 8 Detailed estimation results for bad jobs in the long term (t+10)

	Model 1B	Model 2B	Model 3B
Bad job, overall (t+1)	0.0640***		
	(0.003)		
Bad job, overall (t+5)	0.221***		
	(0.005)		
Low-intensity bad (t+1)		0.0685***	
		(0.004)	
Medium-intensity bad (t+1)		0.0861***	
		(0.005)	
High-intensity bad (t+1)		0.0585***	
		(0.003)	
Low-intensity bad (t+5)		0.172***	
		(0.005)	
Medium-intensity bad (t+5)		0.236***	
		(0.007)	
High-intensity bad (t+5)		0.275***	
		(0.007)	
Wage very low (t+1)			0.0660***
			(0.005)
Wage low (t+1)			0.0488***
			(0.005)
Wage medium (t+1)			0.0238***
			(0.005)
Hours <3 months (t+1)			0.0136***
			(0.003)
Hours 3-6 months (t+1)			0.0423***
			(0.004)
Hours 6-11 months (t+1)			0.0288***
			(0.003)
Contracts 4+ (t+1)			0.0262***
			(0.004)
Contracts 3 (t+1)			0.0216***
			(0.004)
Contracts 2 (t+1)			0.00717*
			(0.003)
Wage very low (t+5)			0.231***
			(0.006)
Wage low (t+5)			0.161***
			(0.005)
Wage medium (t+5)			0.0972***
			(0.004)
Hours <3 months (t+5)			0.277***

	Model 1B	Model 2B	Model 3B
			(0.007)
Hours 3-6 months (t+5)			0.222***
			(0.006)
Hours 6-11 months (t+5)			0.118***
			(0.004)
Contracts 4+ (t+5)			0.0730***
			(0.004)
Contracts 3 (t+5)			0.0421***
			(0.004)
Contracts 2 (t+5)			0.0289***
			(0.003)
Age at entry 16-18	0.0570***	0.0545***	0.0261***
	(0.004)	(0.004)	(0.004)
Age at entry 19-21	0.0126***	0.0117***	-0.00994**
	(0.003)	(0.003)	(0.004)
Age at entry 22-24	-0.0169***	-0.0166***	-0.0237***
	(0.004)	(0.004)	(0.004)
Unemp. rate at entry	-0.00862***	-0.00843***	-0.00868***
	(0.000)	(0.000)	(0.000)
Female	0.0553***	0.0564***	0.0428***
	(0.003)	(0.003)	(0.003)
Agri-fishing	0.0832***	0.0801***	0.0550***
	(0.017)	(0.017)	(0.016)
Construction	0.110***	0.111***	0.0954***
	(0.006)	(0.006)	(0.006)
Trade	-0.00165	-0.00294	-0.0257***
	(0.004)	(0.004)	(0.004)
Hospitality	0.0980***	0.0930***	0.0632***
	(0.006)	(0.006)	(0.005)
Education	-0.0629***	-0.0663***	-0.0676***
	(0.006)	(0.006)	(0.007)
Health	-0.0451***	-0.0464***	-0.0367***
	(0.005)	(0.005)	(0.006)
Observations	125,215	125,215	125,215

Note: standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1. The model also controls for the region of first affiliation and the unemployment rate at entry. The reference categories are as follows: age group 25+, industry sector, and the region of Madrid (regional variables not shown); highest hourly wage group (fourth quartile); highest working hours group (equivalent to eleven or more months worked full time); and lowest rotation group (just one contract in the analysed period). Full estimation results available upon request.

Appendix C: Estimation tables of the annual model

Table 9 Estimation tables of the annual model in t+5

	1997	1998	1999	2000	2001	2002	2003	2004	2005
Bad job, overall (t+1)	0.208***	0.228***	0.221***	0.233***	0.230***	0.241***	0.212***	0.224***	0.261***
	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)	(0.009)
Age at entry 16-18	0.167***	0.148***	0.151***	0.115***	0.150***	0.118***	0.193***	0.211***	0.143***
	(0.016)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.012)
Age at entry 19-21	0.0791***	0.0670***	0.0765***	0.0598***	0.0751***	0.0400***	0.101***	0.105***	0.0555***
	(0.013)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)
Age at entry 22-24	0.0101	0.00423	0.0158	-0.0125	-0.0189	-0.0151	0.00728	0.0183	-0.00635
	(0.014)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.012)
Female	0.0939***	0.0967***	0.106***	0.0997***	0.0718***	0.0542***	0.0516***	0.0373***	0.0307***
	(0.010)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)
Agri-fishing	0.208**	0.145*	0.029	0.0952	0.207***	0.132**	0.123*	0.118*	0.0742
	(0.079)	(0.073)	(0.066)	(0.070)	(0.054)	(0.051)	(0.051)	(0.054)	(0.053)
Construction	0.0303	0.00845	0.0186	0.000586	0.00591	0.0746***	0.107***	0.0984***	0.137***
	(0.018)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.019)	(0.019)	(0.017)
Trade	0.00266	-0.016	-0.00938	-0.00244	0.0154	0.0302*	0.0087	-0.000802	-0.0148
	(0.014)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.016)	(0.016)	(0.016)
Hospitality	0.132***	0.110***	0.133***	0.120***	0.0892***	0.130***	0.170***	0.121***	0.116***
	(0.027)	(0.022)	(0.018)	(0.019)	(0.018)	(0.019)	(0.021)	(0.021)	(0.018)
Education	0.0111	-0.0188	0.00943	0.0019	0.0351	0.0328	0.00301	-0.0272	-0.0623*
	(0.030)	(0.026)	(0.024)	(0.025)	(0.025)	(0.027)	(0.028)	(0.028)	(0.027)
Health	0.103***	0.0818***	-0.0119	-0.0374	-0.0377	0.0269	-0.0362	-0.0148	-0.0543*
	(0.026)	(0.023)	(0.020)	(0.021)	(0.021)	(0.022)	(0.022)	(0.023)	(0.022)
Observations	7995	10200	12608	12283	11065	10556	9679	9823	12259
Predicted prob. of bad jobs in t+5, ref. group [1]	0.1392377	0.1296538	0.1505275	0.1525582	0.1346923	0.1303628	0.1726285	0.1982775	0.2367443

(cont.)

	2006	2007	2008	2009	2010	2011	2012	2013
Bad job, overall (t+1)	0.320***	0.326***	0.331***	0.369***	0.365***	0.317***	0.299***	0.244***
	(0.010)	(0.012)	(0.014)	(0.016)	(0.015)	(0.015)	(0.015)	(0.013)
Age at entry 16-18	0.199***	0.180***	0.214***	0.178***	0.160***	0.202***	0.201***	0.243***
	(0.015)	(0.016)	(0.019)	(0.022)	(0.022)	(0.023)	(0.024)	(0.023)
Age at entry 19-21	0.111***	0.105***	0.119***	0.0954***	0.0616***	0.0895***	0.0779***	0.108***
	(0.014)	(0.015)	(0.017)	(0.020)	(0.018)	(0.018)	(0.018)	(0.017)
Age at entry 22-24	0.0007	-0.0213	-0.00568	0.0476*	-0.00997	0.00786	-0.0443*	-0.00778
	(0.016)	(0.017)	(0.019)	(0.022)	(0.021)	(0.019)	(0.019)	(0.017)
Female	0.0473***	0.0608***	0.0710***	0.0438**	0.0531***	0.0958***	0.0989***	0.0653***
	(0.010)	(0.011)	(0.012)	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)
Agri-fishing	0.085	0.0799	0.0809	0.139	0.112	0.0398	0.249*	0.0286
	(0.060)	(0.059)	(0.062)	(0.075)	(0.081)	(0.088)	(0.104)	(0.088)
Construction	0.126***	0.120***	0.146***	0.155***	0.0328	0.0798	0.131*	-0.000187
	(0.020)	(0.024)	(0.032)	(0.040)	(0.042)	(0.046)	(0.053)	(0.041)
Trade	0.0117	0.0215	0.0436	0.0659*	0.0421	0.0507	0.0802**	0.0714**
	(0.017)	(0.020)	(0.025)	(0.032)	(0.029)	(0.029)	(0.029)	(0.025)
Hospitality	0.126***	0.123***	0.175***	0.168***	0.142***	0.135***	0.187***	0.167***
	(0.020)	(0.022)	(0.026)	(0.032)	(0.029)	(0.030)	(0.029)	(0.026)
Education	-0.0225	-0.0152	0.0393	0.0169	0.07	0.0577	0.0646	0.0471
	(0.028)	(0.029)	(0.034)	(0.040)	(0.038)	(0.036)	(0.037)	(0.031)
Health	-0.0011	-0.00492	0.0466	0.047	0.0178	0.0367	0.0212	0.0351
	(0.024)	(0.025)	(0.030)	(0.035)	(0.034)	(0.035)	(0.036)	(0.031)
Observations	9775	8423	6067	4426	5066	5318	4948	6440
Predicted prob. of bad jobs in t+5, ref. group [1]	0.2427774	0.2738885	0.2819357	0.2576078	0.2009586	0.1966587	0.1996169	0.2083698

Note: standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1. The model also controls for the region of first affiliation. [1] The reference group refers to individuals not in bad jobs in t+1. Full estimation results available upon request.

Table 10 Estimation tables of the annual model in t+10

	1997	1998	1999	2000	2001	2002
Bad job, overall (t+1)	0.0481***	0.0558***	0.0643***	0.0605***	0.0584***	0.0777***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Bad job, overall (t+5)	0.166***	0.170***	0.163***	0.210***	0.218***	0.287***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age at entry 16-18	0.0624***	0.101***	0.0845***	0.0965***	0.0711***	0.0443***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age at entry 19-21	0.0129	0.0403***	0.0265**	0.0544***	0.0173	-0.00616
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age at entry 22-24	-0.00223	-0.00363	-0.00247	0.0112	-0.0266*	-0.0373**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female	0.0890***	0.0705***	0.0531***	0.0448***	0.0537***	0.0257**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Agri-fishing	0.0251	-0.0162	0.0328	0.0737	0.053	-0.0521
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)
Construction	0.0535***	0.0607***	0.105***	0.140***	0.144***	0.174***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Trade	0.000115	-0.0157	-0.0211	-0.0102	-0.0157	-0.0198
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Hospitality	0.109***	0.0495*	0.0483**	0.114***	0.0890***	0.0882***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Education	-0.0497*	-0.0595**	-0.0821***	-0.0823***	-0.0983***	-0.120***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Health	-0.0447**	-0.0603***	-0.0911***	-0.0628***	-0.0369*	-0.0824***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Observations	8,022	10,015	12,155	11,697	10,465	9,822
Predicted prob. of bad jobs in t+10, ref. group (in t+1) [1]	0.1041858	0.1265281	0.1375594	0.1684944	0.1875125	0.2178434
Predicted prob. of bad jobs in t+10, ref. group (in t+5) [2]	0.0860846	0.11382	0.1310766	0.1443616	0.1639731	0.1890105

(cont.)

	2003	2004	2005	2006	2007	2008
Bad job, overall (t+1)	0.0781***	0.0695***	0.0833***	0.0691***	0.0650***	0.0784***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Bad job, overall (t+5)	0.297***	0.289***	0.316***	0.249***	0.243***	0.240***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age at entry 16-18	0.0765***	0.0751***	0.00701	0.0520***	0.00654	-0.0261
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Age at entry 19-21	0.0382**	0.00385	-0.0244*	0.0129	0.00134	-0.0432**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Age at entry 22-24	-0.00398	-0.00108	-0.0310**	-0.0131	-0.0132	-0.0427*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Female	0.0438***	0.0410***	0.0551***	0.0576***	0.0831***	0.104***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Agri-fishing	0.115	0.0598	0.152**	0.207***	0.163**	0.177*
	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.07)
Construction	0.179***	0.0986***	0.134***	0.0711**	0.0298	0.0292
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
Trade	0.00162	0.0161	-0.00503	0.0479**	0.0502**	0.0288
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Hospitality	0.112***	0.118***	0.104***	0.134***	0.147***	0.121***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Education	-0.0493*	-0.0223	-0.0741***	-0.026	-0.0306	-0.0609*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Health	-0.0281	-0.0246	-0.0471**	-0.0158	-0.0193	-0.0186
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	8,908	9,197	11,799	9,314	8,283	6,215
Predicted prob. of bad jobs in t+10, ref. group (in t+1) [1]	0.2289642	0.2234613	0.2408069	0.2171557	0.2220278	0.2151023
Predicted prob. of bad jobs in t+10, ref. group (in t+5) [2]	0.1898453	0.1701981	0.1688915	0.1486352	0.1432973	0.1427359

Note: standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The model also controls for the region of first affiliation. [1] The reference group refers to individuals not in bad jobs in t+1. [2] The reference group refers to individuals not in bad jobs in t+5. Full estimation results available upon request.

Appendix D: Sensitivity analysis

D.1: Redefining the utility function

Table 11 Estimation results for bad jobs in the medium (t+5) and long term (t+10) under different definitions of the utility function

	Bad job in t+5		Bad job in t+10	
	Model 1A' (r=4)	Baseline Model 1A (r=2)	Model 1B' (r=4)	Baseline Model 1B (r=2)
Bad job overall (t+1)	0.203***	0.218***	0.0560***	0.0640***
	(0.002)	(0.002)	(0.003)	(0.00)
Bad job overall (t+5)			0.218***	0.221***
			(0.006)	(0.005)
Age at entry 16-18	0.128***	0.145***	0.0455***	0.0570***
	(0.003)	(0.004)	(0.004)	(0.004)
Age at entry 19-21	0.0595***	0.0724***	0.00726*	0.0126***
	(0.003)	(0.003)	(0.003)	(0.003)
Age at entry 22-24	-0.00705*	-0.00417	-0.0157***	-0.0169***
	(0.003)	(0.003)	(0.003)	(0.004)
Female	0.0577***	0.0630***	0.0564***	0.0553***
	(0.002)	(0.002)	(0.003)	(0.003)
Agri-fishing	0.109***	0.107***	0.0765***	0.0832***
	(0.014)	(0.015)	(0.017)	(0.017)
Construction	0.0644***	0.0674***	0.108***	0.110***
	(0.005)	(0.005)	(0.006)	(0.006)
Trade	0.0236***	0.0233***	-0.00375	-0.00165
	(0.004)	(0.004)	(0.004)	(0.004)
Hospitality	0.125***	0.131***	0.0802***	0.0980***
	-0.00464	(0.005)	(0.005)	(0.006)
Education	0.0148*	0.0193**	-0.0635***	-0.0629***
	(0.006)	(0.007)	(0.006)	(0.006)
Health	-0.0128*	0.0263***	-0.0593***	-0.0451***
	(0.005)	(0.006)	(0.005)	(0.005)
Observations	161,395	161,395	125,215	125,215

Note: standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Full estimation results available upon request. For Model A2 and the baseline model for the long run, post-2008 entrants are not regarded in this model, as it is lack of data availability, in first instance, rather than selection bias what explains these cohorts not being included in the database.

D.2: Resetting the reference year to define bad jobs

Table 12 Estimation results for bad jobs in the medium (t+5) and long term (t+10) under different benchmark years for the categorisation of bad jobs

	Bad job in t+5		**Bad job in t+10**	
	Model 1A'' (threshold 2016)	Baseline Model 1A (threshold 2007)	Model 1B'' (threshold 2016)	Baseline Model 1B (threshold 2007)
Bad job overall (t+1)	0.234***	0.218***	0.0560***	0.0700***
	(0.002)	(0.002)	(0.003)	(0.003)
Bad job overall (t+5)			0.218***	0.233***
			(0.006)	(0.005)
Age at entry 16-18	0.149***	0.145***	0.0455***	0.0590***
	(0.004)	(0.004)	(0.004)	(0.004)
Age at entry 19-21	0.0758***	0.0724***	0.00726*	0.0133***
	(0.003)	(0.003)	(0.003)	(0.003)
Age at entry 22-24	-0.00593	-0.00417	-0.0157***	-0.0157***
	(0.003)	(0.003)	(0.003)	(0.004)
Female	0.0666***	0.0630***	0.0564***	0.0580***
	(0.002)	(0.002)	(0.003)	(0.003)
Agri-fishing	0.110***	0.107***	0.0765***	0.0888***
	(0.015)	(0.015)	(0.017)	(0.017)
Construction	0.0698***	0.0674***	0.108***	0.113***
	(0.005)	(0.005)	(0.006)	(0.006)
Trade	0.0247***	0.0233***	-0.00375	0.0000208
	(0.004)	(0.004)	(0.004)	(0.004)
Hospitality	0.137***	0.131***	0.0802***	0.104***
	(0.005)	(0.005)	(0.005)	(0.006)
Education	0.0174**	0.0193**	-0.0635***	-0.0666***
	(0.007)	(0.007)	(0.006)	(0.006)
Health	0.0267***	0.0263***	-0.0593***	-0.0435***
	(0.006)	(0.006)	(0.005)	(0.005)
Observations	161395	161395	125215	125215

Note: standard errors in parentheses: *** p < 0.01, ** p < 0.05, * p < 0.1. Full estimation results available upon request. For Model A4 and the baseline model for the long run, post-2008 entrants are not regarded in this model, as it is lack of data availability, in first instance, rather than selection bias what explains these cohorts not being included in the database.