Dual Returns to Experience[*]

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Abstract

In this paper we study human capital accumulation and wage trajectories of young workers in a dual labor market. Using rich administrative data for Spain, we follow workers since labor market entry to measure experience accumulated under different contractual arrangements and relate it to current wages. We show that returns to experience accumulated in fixed-term contracts are, on average, lower than the returns to experience acquired in permanent jobs. However, this gap masks significant heterogeneity across individuals. The gap in returns widens along the skill distribution, where workers in the upper tail have the largest difference in returns. Moreover, among equally experienced workers, higher incidence of temporary employment in the past is associated with substantially lower wages. Ultimately, heterogeneous returns to experience translate into significant changes in the position of workers along the distribution of wage growth after 15 years in the labor market, bearing implications for life-cycle wage inequality.

Keywords: human capital, labor market duality, earnings dynamics.

JEL codes: J30, J41, J63.

1 Introduction

Fixed-term contracts are widespread in many European countries (ter Weel, 2018). Their extensive use is often rationalized by employers' quest for flexibility in rigid labor markets (Aguirregabiria and Alonso-Borrego, 2014). On the one hand, workers might benefit from the availability of fixed-term contracts since they ease job finding (de Graaf-Zijl et al., 2011) and mitigate wage losses associated with skill depreciation during non-employment (Guvenen et al., 2017; Jarosch, 2021). On the other hand, temporary employment could be detrimental if induces unstable careers (Blanchard and Landier, 2002) and lower human capital accumulation (Cabrales et al., 2017; Bratti et al., 2021). While temporary contracts might reduce time out of work and allow workers to accumulate experience (almost) continuously, the quality of that experience may be worse due to poorer learning opportunities that still translate into foregone wages.

In this paper we shed light on how labor market duality affects human capital accumulation and wage trajectories of workers during their first years in the labor market. We perform our analysis in the context of the Spanish labor market, where the use of fixed-term contracts is the rule rather than the exception: more than 90% of the contracts signed each month are fixed-term and around 25% of the workforce is under some form of temporary employment (Felgueroso et al., 2018). We rely on rich administrative data that allows us to follow individuals since labor market entry and measure exact time worked under permanent and temporary contracts, separately. We use these precise measures of accumulated experience to estimate reduced-form wage regressions derived from a stylized framework of human capital development in a dual labor market.

Our results point to lower returns to past experience under fixed-term contracts relative to open-ended contracts. In particular, we find that each additional year of accumulated experience in temporary employment is associated with 0.8 percentage points lower daily wage relative to the experience accumulated in permanent jobs, after accounting for observed match components and unobserved worker heterogeneity. Differences in returns prevail among job switchers, suggesting a human capital channel, since for these workers there is a clear dissociation between where experience was acquired and where it is valued. However, the uncovered difference masks substantial heterogeneity among workers. We find that the gap in returns is increasing with individual ability, being negligible for individuals at the bottom of the ability distribution while reaching 1.6 percentage points for high-ability workers. Similarly, while individuals with low levels of experience do not

suffer losses, higher incidence of past temporary employment among highly experienced workers leads to wage losses of up to 15%. Finally, the comparison of contract-specific employment trajectories indicates that heterogeneous returns to experience are associated with large shifts along the distribution of wage growth after 15 years since labor market entry.

This paper contributes to different strands of the literature. A significant body of research has investigated the consequences of flexibility at the margin (existence of fixed-term contracts with low firing costs alongside highly protected open-ended contracts) for labor market performance (Boeri, 2011; Bentolila et al., 2020). One of the dimensions analyzed is the impact of temporary employment on workers' careers. Although empirical evidence on whether temporary employment is a stepping stone or a dead end to stable employment are mixed (Filomena et al., 2021), what is less controversial is that fixed-term contracts penalize workers in the long run, due to a less continuous employment path and lower wage growth (Booth et al., 2002; Autor and Houseman, 2010; García-Pérez et al., 2019). We complement this literature by showing that even if workers are able to be continuously working over their career, they are penalized from acquiring experience in fixed-term contracts.

A parallel strand of the literature has analyzed contemporaneous wage differentials between temporary and permanent workers (e.g., Booth et al., 2002; de la Rica, 2004; Mertens et al., 2007; Kahn, 2016; Laß and Wooden, 2019; Albanese and Gallo, 2020). Most of the results point to a penalty for workers on fixed-term contracts, which is typically rationalized by either less firm-sponsored training (Arulampalam and Booth, 1998; Cabrales et al., 2017; Bratti et al., 2021) or lower worker's effort when the probability of conversion from temporary to permanent are low (Sanchez and Toharia, 2000; Dolado et al., 2016). Our analysis complements this literature by focusing on how past experience accrued on temporary versus permanent contracts affects current wages. Our results suggest that the costs of being employed on temporary contracts accumulate over workers' careers, leading to lower returns to experience if on-the-job learning occurs under fixed-term contracts.

Finally, our analysis contributes to a growing literature that investigates the existence of heterogeneous returns to experience due to differences in learning opportunities based on firm type (Pesola, 2011; Arellano-Bover and Saltiel, 2021), coworkers quality (Jarosch et al., 2021), or city size (de la Roca and Puga, 2017). We add to this line of work by

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showing that skill acquisition under alternative contractual arrangements also leads to heterogeneous wage-experience profiles.

The remainder of the paper proceeds as follows. Section 2 presents the conceptual framework behind our reduced-form analysis, while Section 3 describes the data. Section 4 introduces our econometric approach and discusses the results. Section 5 concludes.

2 Earnings Trajectories in a Dual Labor Market

In this section we lay out a parsimonious framework linking labor market duality to on-the-job human capital accumulation and wage growth, which we use to derive our main earnings equation.

Human Capital. Consider an individual i in period t. We define the stock of human capital for this individual as

$$H_{it} = \eta_i + h_{it} \tag{1}$$

where η_i is the human capital developed before labor market entry (education level but also innate ability) and assumed to be fixed over time while h_{it} is the stock of human capital accumulated since labor market entry up period t.

Human capital, h_{it}, is acquired on the job and varies according to the type of contract worker i is employed in at time t. Formally, skill acquisition between two consecutive periods is governed by the following low of motion

$$h_{it+1} = h_{it} + \mu_{it}^c \tag{2}$$

where c denotes the type of contract, fixed-term vs open-ended, and μ_{it}^c is an i.i.d. draw from contract-specific distribution F^c, such that $\mathbf{E}[\mu_{it}^c] = \gamma^c$. Differences in human capital accumulation between workers with fixed-term and open-ended contracts are governed by differences in the distributions of F^c. For example, companies may be less willing to invest in people employed on temporary contracts due to the potential finite nature of the labor relationship (Crawford, 1988; Poulissen et al., 2021), which translates into worse skill acquisition for workers during temporary employment episodes.[1] Workers on fixed-term contracts may also be less willing to make an effort to learn on the job

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[1] Ferreira et al. (2018) show that although workers on temporary contracts are less likely to receive *formal* training, they participate more actively in informal learning than their peers in permanent contracts. This higher commitment to informal training is especially acute at the beginning of their careers to secure a permanent contract.

if the likelihood of contract conversion is low (Dolado et al., 2016). In the absence of differences in skill acquisition among workers employed under different type of contracts, human capital accumulation would depend exclusively on the total experience acquired on the job.

In our stylized framework the current stock of human capital accumulated since labor market entry depends on the employment history across different contracts:

$$h_{it} = \sum_{k=1}^{t-1} \mu_{ik}^{c(i,k)} \tag{3}$$

and

$$\mathbf{E}[h_{it}|\mathbf{oec}_{it}, \mathbf{ftc}_{it}] = \sum_{k=1}^{t-1} \sum_{m \in \{\text{ftc}, \text{oec}\}} \mathbf{1}[c(i,k) = m]\gamma^m \tag{4}$$

where $\mathbf{oec}_{it}$ and $\mathbf{ftc}_{it}$ are the complete histories in open-ended and fixed-term contracts since labor market entry up until time t, while $\mathbf{1}[c(i,k) = m]$ is an indicator function equal to one if worker i was employed under a fixed-term (ftc) or open-ended contact (oec) in period k.[2]

Earnings. The structure of (log) earnings of worker i at period t is governed by the following process

$$\ln w_{it} = \eta_i + h_{it} + X_{it}\Omega \tag{5}$$

where η_i is the individual specific component, h_{it} stands for the stock of human capital acquired up to time t, and X_{it} reflects the contemporaneous job characteristics. Thus, the expected earnings are given by

$$\mathbf{E}[\ln w_{it}|i, X_{it}, \mathbf{oec}_{it}, \mathbf{ftc}_{it}] = \eta_i + \gamma^{\text{oec}}\text{oec}_{it} + \gamma^{\text{ftc}}\text{ftc}_{it} + X_{it}\Omega \tag{6}$$

where oec_{it} and ftc_{it} are measures of accumulated experience under open-ended and fixed-term contracts since labor market entry up until time t, defined respectively as

$$\text{ftc}_{it} = \sum_{k=1}^{t-1} \mathbf{1}[c_{c(i,k)} = \text{ftc}] \qquad \text{and} \qquad \text{oec}_{it} = \sum_{k=1}^{t-1} \mathbf{1}[c_{c(i,k)} = \text{oec}]$$

The sum of oec_{it} and ftc_{it} represents the standard experience component in a Mincer regression (Mincer, 1974), which does not differentiate returns across contracts.

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[2]Individuals may have more than one job at any given time. In our empirical analysis, we count all days worked under a given type of contract each year independently of whether is with the same employer or under multiple ones.

Empirical Hypothesis. In this framework, we test two hypotheses relating wage trajectories in a dual labor market. Wage trajectories over the life cycle depend on human capital accumulation, which is affected by on-the-job learning opportunities and employers' investment in skills. To the extent the latter are higher in open-ended contracts, we should observe a larger return to experience accumulated in this type of contract. The first hypothesis makes this claim:

Hypothesis 1: Human capital accumulates faster under open-ended contracts.

Wage profiles are heterogeneous across workers and steeper for highly educated or more skilled individuals (Heckman et al., 2006). To the extent these workers either learn faster on the job or receive more training, we should observe a larger penalties from accumulating experience in temporary contracts for high-ability workers. The second hypothesis is as follows:

Hypothesis 2: The gap in returns increases with individual ability.

Ultimately, it is an empirical question whether we find any difference in the returns to experience accumulated in permanent and temporary contracts. This is what we explore in the remainder of the paper.

3   Data

Our main data source is the Spanish Continuous Sample of Employment Histories (*Muestra Continua de Vidas Laborales* or MCVL), an administrative dataset collected annually by the Spanish Social Security administration and linked to the Residents' Registry and Tax Records since 2005 up to 2018.[3] The MCVL is a representative 4 percent random sample of individuals who had any relationship with the Social Security at any time in the reference year.[4] The dataset has a longitudinal design, since an individual present in a year and subsequently remains registered with the Social Security administration stays

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[3]The first version of the MCVL corresponds to 2004. This wave is discarded as most of the information structure differs from that available for subsequent years.

[4]This includes employed and self-employed workers, recipients of unemployment benefits and pension earners, but excludes individuals registered only as medical care recipients, or those with a different social assistance system (civil servants, such as the armed forces or the judicial power).

as a sample member.[5] The MCVL is refreshed each year, remaining representative of both the stock and flows of individuals.

For each sample member, the MCVL retrieves *all* relationships with the Social Security since the date of the first job spell, or 1967 for earlier entrants. All job spells are followed from their start up to their end or to the 31st of the December of 2018. This unique feature allows us to track individuals over time and calculate the exact number of days worked since labor market entry. For each employment episode, we observe detailed information on the labor relationship including part-time status, occupation category, workplace location and sector of activity, type of contract (with reliable information since 1997), and labor income.[6] Demographic information is also reported, e.g. age, gender, education, nationality.[7]

We use the 2005-2018 MCVL original files to identify potential individuals for our estimation sample. We exclude individuals with missing key information and focus on those who entered the labor market after 1996 to be able to track days worked under alternative job contracts. We exclude from the sample all foreigners because we do not have information on any previous work experience abroad, so we cannot compute their complete labor market history. Similarly, we remove individuals whose first employment observations is more than 5 years after predicted graduation year, i.e. labor market entry. We further restrict the sample to employees in the General Regime of the Social Security, thereby excluding employment episodes in special regimes such as agriculture, fishing, mining, or household activities as well as of self-employment. From this sample of job spells, we construct an individual-year panel to study individual wages up to the first 15 years after predicted graduation.[8] These restrictions yield a final sample of 242,774 individuals observed over a total of 1,954,097 employment (work-year) observations between 1997 and 2018. Table A.1 in the Appendix reports descriptive statistics.

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[5]Individuals who stop working remain in the sample while they receive unemployment benefits or other welfare benefits (e.g. retirement pension). Individuals leave the sample when they die or leave the country permanently. Likewise, each wave adds individuals who enter the labor market for the first time.

[6]Labor income comes from Social Security contribution bases that are top-coded. We correct the upper tail of the wage distribution by fitting cell-by-cell Tobit models to log daily wages. Appendix B provides a detailed discussion on the correction method and offers a comparison between original and corrected wage distributions.

[7]Appendix C provides a detailed description of the variables.

[8]If an individual has more than one labor relationship with different employers, we keep only the main employer defined as the one reporting the highest annual earnings. Similarly, if an individual hold more than one contract with the same employer within a year, we select the job characteristics coming from the last job contract observed in that year.

4   Returns to Experience in a Dual Labor Market

4.1   Econometric Model

Returns to Experience.   The stylized framework in Section 2 provides us with a flexible specification to estimate the returns to experience under different type of contracts. To this purpose we adapt equation (6) and estimate a linear panel data model for the logarithm of real daily wages of individual i and year t

$$\ln w_{it} = \eta_i + \sum_{c \in \{\text{ftc,oec}\}} \gamma^c c_{it} + X_{it}\Omega + \delta_e + \delta_t + \epsilon_{it} \tag{7}$$

where η_i stands for pre-labor market permanent individual ability while oec_{it} and ftc_{it} measure the experience accumulated by worker i working under open-ended or fixed-term contracts respectively, since labor market entry up to time t.[9] X_{it} refers to contemporaneous job-firm characteristics (tenure, type of contract, part-time status, skill level, plant size and age, location, and sector of activity), whereas δ_e and δ_t are potential experience and year fixed effects, respectively.[10] The inclusion of potential experience effects along with contemporaneous job-firm characteristics ensures that differences in the returns to accumulated experience can only be driven by heterogeneous past histories in the labor market. Individual fixed effects are intended to account for the sorting of workers based on unobserved permanent heterogeneity. Under the assumption that ϵ_{it} is an i.i.d. random term, consistent estimates can be obtained by applying the standard panel fixed effects estimator.[11]

Unobserved Learning Abilities.   To explore complementarities between individual ability and experience acquired in different contracts, we introduce worker heterogeneity in the form of unobserved ability to learn. More specifically, we incorporate the interaction between ability and the learning benefits of fixed-term and open-ended contracts into our framework and extend equation (7) as follows

$$\ln w_{it} = \eta_i + \sum_{c \in \{\text{ftc,oec}\}} \gamma^c c_{it} + \sum_{c \in \{\text{ftc,oec}\}} \varphi^c \eta_i c_{it} + X_{it}\Omega + \delta_e + \delta_t + \epsilon_{it} \tag{8}$$

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[9]For simplicity, we only include experience terms linearly but we also estimate Equation (7) using a step-wise specification for contract-specific returns to experience with 22 cut-off points.

[10]We include potential experience fixed effects, i.e., years since entry into the labor market, rather than age effects because some age groups are only identified by the less educated individuals. For example, college graduates are not observed before reaching the age of 24. In addition, accounting for potential experience effects ensures that we are comparing individuals at the same point in their careers.

[11]For comparison we also estimate a version of this model without individual fixed effects, including education level and a female indicator to control for pre-labor market human capital.

where we allow the value of experience accumulated in different contracts to vary among individuals. The parameter φ^c captures whether higher-ability workers face larger returns to experience acquired at different contracts. To estimate equation (8) we follow the algorithm proposed by de la Roca and Puga (2017).[12]

Scarring Effects. Differences in returns to contract-specific experience could be due to heterogeneous rates at which experience is accumulated, not just differences in skill acquisition. Workers under temporary contracts may have more job interruptions than individuals employed in permanent positions and non-working episodes could result into lower experience levels (and lower human capital overall). To control for this margin, we adapt our benchmark model and compare individuals with the same level of total experience but different incidence of temporary employment in their career. In particular, each year, we discretize our overall experience measure into Q-bins such that $q = \{\{0\}, (0, 4], (4, 7], (7, 10], (10, 15], ..., (95, 97], (97, 100]\}$ and estimate the following regression model

$$\ln w_{it} = \eta_i + \sum_{m=1}^{3} \sum_{q=0}^{Q} \beta_{m(q)} \mathbb{1}\{\exp_{it} = q\} \times \mathbb{1}\{\text{ftc}_{it} = m\} + X_{it}\Omega + \delta_e + \delta_t + \epsilon_{it} \quad (9)$$

where $\mathbb{1}\{exp_{it} = q\}$ takes value one if worker i falls into the qth-bin of actual experience in period t. We then interact this variable with an indicator for the incidence of temporary employment during the acquisition of experience. More precisely, we create three group of workers based on the ratio of experience under fixed-term contracts to overall experience: low (ratio lower than 0.3), medium (between 0.3 and 0.9) and high incidence (above 0.9). Thus, $\mathbb{1}\{\text{ftc}_{it} = m\}$ is an indicator variable identifying workers in a given group according to the incidence of temporary employment since labor market entry up to time t. Notice that the parameters $\beta_{m(q)}$ are only identified up to a normalization. We impose the impact of accumulated experience on individuals wages to be zero for the first observation, when experience in the labor market is equal to zero. This implies that $\beta_{m(0)}$ is equal to zero for each of the three m-groups, thereby estimating for each m-group 22 parameters. The point estimates $\beta_{2(q)}$ and $\beta_{3(q)}$ capture the wage gap between individuals who have been employed for the same amount of time since labor market entry but have had a higher

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[12]The algorithm requires to guess a set of individual fixed effects, η_i^0, estimate equation (8) by OLS, obtain a new set of estimates of worker fixed effects as

$$\eta_i^1 = \frac{\ln w_{it} - \sum_{c \in \{\text{ftc,oec}\}} \gamma^c c_{it} - X_{it}\Omega - \delta_e - \delta_t}{\sum_{c \in \{\text{ftc,oec}\}} \varphi^c c_{it}}$$

and use them as new guess until convergence is achieved.

incidence of temporary employment in the past. Hence equation (9) allows us to quantify the value of experience in fixed-term contracts relative to permanent contracts, comparing workers with the same level of experience acquired under different work histories due to the heterogeneous incidence of temporary employment.

4.2 Results

Dual Returns to Experience. We start our discussion on how skill acquisition under different type of contracts affect wages by looking at the returns to experience estimated from Equation (7). To ease the interpretation, we estimate standard Mincerian returns to experience and then differential returns by type of contract, with and without individual-level unobserved heterogeneity. The results, displayed in Table 1 Panel A, show that each additional year of experience raises individual wages by 2.9%, or by 4.9% if both contemporaneous job-firm characteristics and individual heterogeneity are taken into account. However, the returns to experience vary depending on whether such experience was accumulated under fixed-term (FTC) or open-ended (OEC) contracts. Consistent with the first hypothesis, an additional year of experience in permanent contracts is associated with wage gains of 3.5%, while returns are 1.5 percentage points (pp) lower for experience accumulated in temporary jobs. The difference is reduced once unobserved individual heterogeneity is factored in ($\sim$0.8pp), suggesting that the sorting of workers into contractual arrangements (and other *observed* match components) is important, but does not fully explain the gap in returns.[13] To the extent the link between current wages and past experience reveals past skill development of workers, our findings are consistent with lower on-the-job learning while employed under FTC.

To strengthen our findings, we look at the first re-employment observation of workers who switched jobs in our sample (see Table 1 Panel B). In this fashion, we can dissociate the place where experience has been accumulated from the place where that experience is being valued and thus shed light on the human capital channel. The results are aligned with our baseline estimates: returns to experience acquired under OEC are higher relative to FTC experience ($\sim$0.6pp gap). This supports the idea of contract-specific on-the-job learning, which implies lower accumulation of human capital during temporary employ-

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[13]Our results are robust to alternative measures of labor income (Table A.2) as well as different specifications to account for life-cycle differences such a cubic polynomial on potential experience, excluding potential experience fixed-effects, or using age fixed effects (Table A.3). Heterogeneous returns to experience also arise when modelling contract-specific experience non-parametrically using step functions with 22 cut-off points, but the gap between OEC and FTC is non-linear (Figure A.1).

ment episodes.

Table 1: Dual Returns to Experience

A. All Workers	OLS		Fixed-Effects	
	(1)	(2)	(3)	(4)
Experience	0.0293***		0.0496***	
	(0.0003)		(0.0005)	
Experience OEC		0.0350***		0.0499***
		(0.0003)		(0.0005)
Experience FTC		0.0209***		0.0421***
		(0.0004)		(0.0006)
Observations	1,954,097	1,954,097	1,954,097	1,954,097
R-squared	0.6330	0.6343	0.3058	0.3064
B. Job Switchers	OLS		Fixed-Effects	
	(1)	(2)	(3)	(4)
Experience	0.0303***		0.0482***	
	(0.0003)		(0.0006)	
Experience OEC		0.0347***		0.0492***
		(0.0004)		(0.0006)
Experience FTC		0.0245***		0.0436***
		(0.0004)		(0.0008)
Observations	590,080	590,080	590,080	590,080
R-squared	0.6019	0.6025	0.3432	0.3433

Notes: Experience is measured in days and then it is transformed into years. OEC and FTC stand for experience acquired under open-ended and fixed-term contracts, respectively. All specifications include controls for a quadratic polynomial in tenure, type of contract, a dummy for part-time jobs, indicators for occupation-skill category (2), sector of activity (10), workplace location (50), small and medium enterprises (plant size < 50), young organizations (plant age < 10), potential experience dummies (5), and year dummies (22). OLS regressions include additional controls for education and gender. Standard errors clustered at the individual level in parenthesis. Panel B specification uses only the first re-employment observation after job change. Job switchers = 200,491. *** p<0.01, ** p<0.05, * p<0.1. The R-squared reported in columns (3) and (4) is within workers.

Worker's Observables. We estimate contract-specific returns to experience separately by gender and education level. The results are reported in Table 3. While we find that the returns to experience acquired under permanent contracts are similar for men and women, the baseline patterns seem not to hold among individuals with at most a high-school degree. Our results suggest that non-college graduates face no differential returns to experience based on whether such experience was acquired under FTC or OEC. While college graduates exhibit similar returns to experience in FTCs, they instead enjoy substantially higher returns to experience from permanent jobs, resulting in a larger gap in returns between OEC and FTC-specific experience. In particular, we find that

returns to experience accumulated while working on OECs are 1.6pp higher than returns to experience from temporary employment. Consistent with the second hypothesis, this greater difference may be due to the fact that wage-experience profiles are steeper among highly educated individuals, who can take full advantage of better learning opportunities provided during open-ended jobs.

Table 2: Dual Returns to Experience: Worker's Observables

	Gender		Education	
	Male	Female	Non-College	College
Experience OEC	0.0506***	0.0489***	0.0421***	0.0589***
	(0.0006)	(0.0007)	(0.0005)	(0.0009)
Experience FTC	0.0405***	0.0426***	0.0428***	0.0436***
	(0.0008)	(0.0008)	(0.0007)	(0.0011)
Observations	934,294	1,019,803	1,180,999	773,098
R-squared	0.2870	0.3242	0.3051	0.3053

Notes: Experience is measured in days and then it is transformed into years. OEC and FTC stand for experience acquired under open-ended and fixed-term contracts, respectively. Non-college includes both high-school dropouts and graduates. All specifications include the same set of controls as Column (4) in Table 1. Standard errors clustered at the individual level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The R-squared reported is within workers.

Worker's Unobserved Abilities. Differential returns across education groups suggest that differences in skill acquisition between permanent and temporary jobs are plausibly related to individual ability to learn. To further investigate this link, we use estimates from equation (8) and calculate the returns to experience acquired on OEC and FTC across the distribution of individual (unobserved) ability. Figure 1 shows that both returns are increasing with individual abilities, pointing to a strong complementarity in wages between unobserved skills and acquired experience. However, while past OEC experience has a higher reward on average, the gap in returns is heterogeneous across workers' unobserved skills. We find no significant difference between OEC and FTC experience returns at the bottom of the skill distributions. For instance, for individuals below the 10th percentile of the ability distribution, an additional year of experience is associated with 2.5 percent higher wages, regardless of the type of contract under which that experience was acquired. The gap in returns however increases with individual ability, reaching a difference of 1.6pp for workers at the top of the ability distribution. More specifically, for workers above the 90th percentile of the ability distribution, an

Figure 1: Dual Returns to Experience: Unobserved Ability
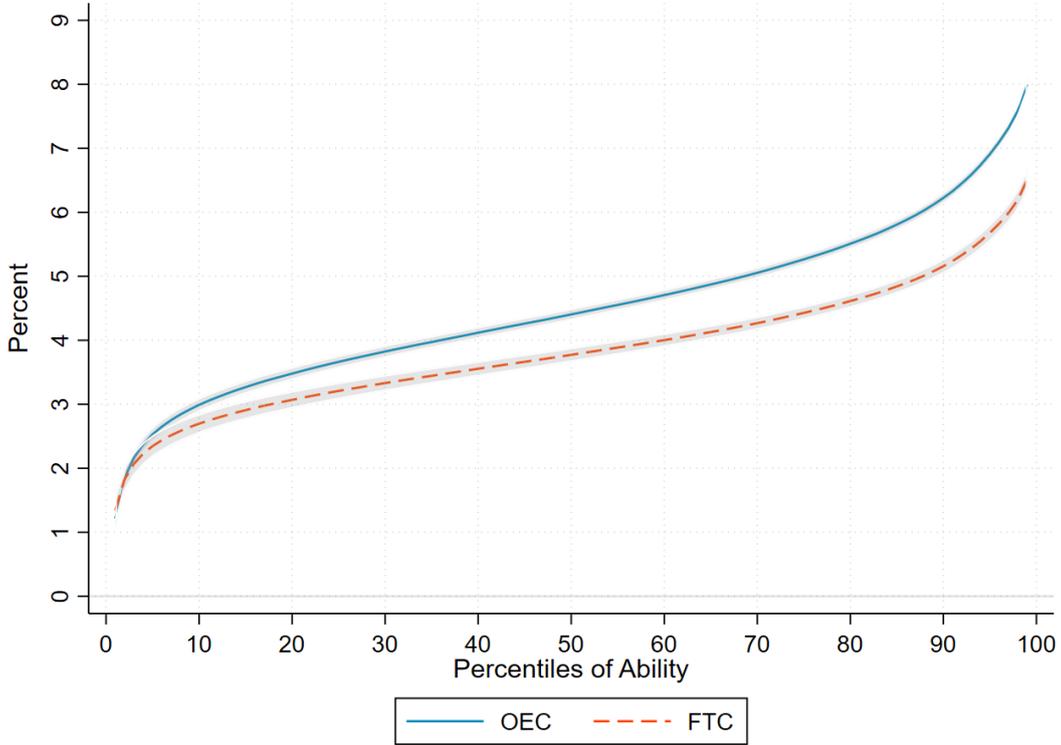
Notes: Contract-specific returns to experience computed for each percentile of unobserved ability using estimates ($\times 100$) from equation (8). 95% confidence bands are calculated using the clustered-wild bootstrap (100 repetitions) procedure by Cameron et al. (2008). OEC and FTC stand for experience acquired under open-ended and fixed-term contracts, respectively.

additional year of OEC (FTC) experience translates into 8% (6.4%) higher earnings.[14]

Scarring Effects.   While temporary employment seems to generate a gap in returns through lower skill acquisition, it could also reduce overall actual experience because of job interruptions and induce skill depreciation. Hence, to shed light on the scarring effects of temporary employment on wages due to less on-the-job learning, we compare workers who have the same actual experience but accumulated differently due to the heterogeneous incidence of temporary contracts since labor market entry up to time t.

Figure 2 plots $\beta_{2(q)}$ and $\beta_{3(q)}$ parameters from equation (9), which can be interpreted as the scarring effects of temporary employment, as they proxy by means of current wages the human capital investment foregone during the acquisition of experience during temporary employment episodes. The estimates reveal several interesting patters. First, we do not find a negative impact of higher incidence of temporary employment among

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[14]We have also experimented with a quantile regression approach to estimate the equation 7. The results are consistent with the existence of heterogeneous returns across the skill distribution: difference in returns widens along the wage distribution. Results are available upon request.

Figure 2: Scarring Effects of Temporary Employment
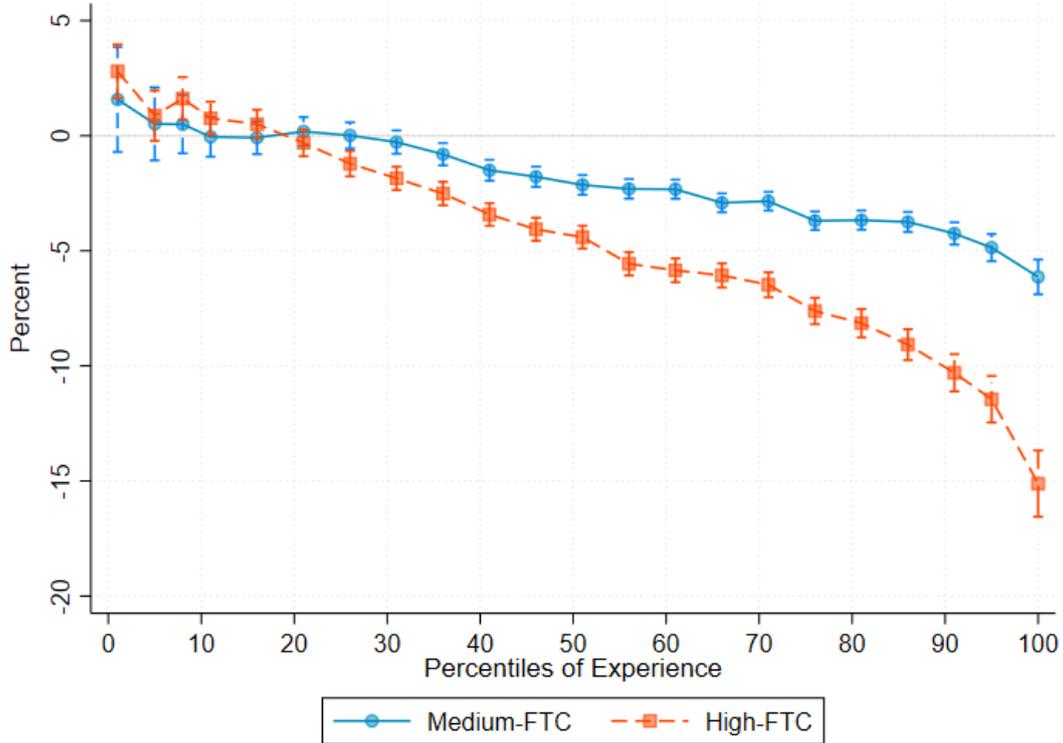
Notes: Estimates ($\times 100$) and 95% confidence intervals of the scarring effects of temporary employment, $\beta_{2(q)}$ and $\beta_{3(q)}$, from equation (9). Standard errors are clustered at the individual level. Medium-FTC (High-FTC) incidence refers to individuals whose actual experience on a temporary contract relative to overall actual experience is between 0.3 and 0.9 (above 0.9).

low experienced individuals. Second, wage losses become apparent from the fortieth percentile of overall experience onward. distribution. Third, the greater the acquisition of experience through fixed-term contracts, the greater the losses. Finally, highly experienced individuals face wage losses of up to 15% due to higher incidence of FTC in the past. These findings are indicative of poorer learning opportunities face by workers during temporary employment episodes which translates into lower earnings.

Counterfactual Wage Trajectories. Finally, we assess how much dual learning on-the-job can affect earnings trajectories. We do this by comparing wage growth 15 years after labor market entry for alternative labor market histories based on the incidence of the two contractual arrangements. Specifically, we use estimates from equation (8) to predict counterfactual wage growth for workers who spent 15 years in OEC and compare it to the alternative scenario when the worker experienced 15 years in FTC. Given the complementarity between ability and returns to experience, we look at low and high ability workers under the two scenarios described above. To put these values in context,

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Table 3: Life-Cycle Wage Trajectories

Unobserved Ability	Employment Trajectory	Counterfactual Wage Growth, %	Actual Wage Growth, Percentiles
10th Percentile	Always in FTC	37.75	40
10th Percentile	Always in OEC	41.86	43
90th Percentile	Always in FTC	72.21	62
90th Percentile	Always in OEC	87.15	73

Notes: Wage growth calculated as the log difference between entry-level daily wages and daily wages observed 15 years after. Counterfactual wage growth is computed for alternative employment trajectories based on the continuous incidence of OEC or FTC and using (unobserved) ability-specific returns from equation 8. Actual wage growth stands for wage growth for workers observed during 15 years in the labor market.

we compare them to the wage growth observed after 15 years of potential experience and report the associated percentile in the distribution.[15]

Table 3 reports the results of this exercise. On the one hand, low-skill workers do not suffer any significant penalty from accumulating experience in FTC. After 15 years since entering the labor market, workers who have always been employed in OEC would face 5pp higher wage growth, allowing them to move only marginally in the wage growth distribution (from the 40th to the 43rd percentile). On the other hand, high-skill workers would significantly suffer from accumulating experience only through FTC. In particular, we find that the wage penalty of being continuously employed under FTC relative to OEC amounts to roughly 15pp, corresponding to a shift from the 73rd to the 62nd percentile of the wage growth distribution.

5 Conclusions

In this paper we document how labor market duality affects human capital accumulation and life-cycle wage profiles of young workers. We implement our analysis in the context of the Spanish labor market, which is characterized by a strong segmentation between fixed-term and open-ended contracts.

Our results point to lower returns to experience acquired while working under fixed-term contracts compared to permanent jobs, suggesting less on-the-job learning during temporary employment episodes. However, the gap in returns shows significant hetero-

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[15]To compute the actual wage growth distribution, we rely only on the oldest cohorts for whom we observed 15 years of potential experience.

geneity among workers. We show that differences increase as a function of individual ability, suggesting a strong complementarity between contract-related learning opportunities and individual ability. We also document substantial wage losses among workers with the same experience who faced a higher incidence of temporary employment in the past, which we take as evidence of foregone income due to lower skill acquisition under fixed-term contracts.

Taken together, our findings suggest numerous policy considerations. Heterogeneous returns across contracts bear implications for life-cycle wage inequality, hence policy targeted at increasing human capital accumulation in temporary contracts (e.g. on-the-job training subsidies) could be beneficial in reducing long-run wage differences. Moreover, our results hint that the negative impact of labor market duality on workers' early careers extends beyond unstable work histories, as experience accumulated while employed under fixed-term contracts is less valuable. While the joint evaluation of both margins along with employer's training choices would require the use of a more structural model, we leave that for future research.

References

Aguirregabiria, V. and Alonso-Borrego, C. (2014). Labor Contracts and Flexibility: Evidence from a Labor Market Reform in Spain. *Economic Inquiry*, 52(2):930–957.

Albanese, A. and Gallo, G. (2020). Buy flexible, Pay More: The Role of Temporary Contracts on Wage Inequality. *Labour Economics*, 64:101814.

Arellano-Bover, J. and Saltiel, F. (2021). Differences in On-the-Job Learning Across Firms. *IZA DP No. 14473*.

Arulampalam, W. and Booth, A. L. (1998). Training and Labour Market Flexibility: Is There a Trade-off? *British Journal of Industrial Relations*, 36(4):521–536.

Autor, D. H. and Houseman, S. N. (2010). Do Temporary-Help Jobs Improve Labor Market Outcomes for Low-Skilled Workers? Evidence from "Work First". *American Economic Journal: Applied Economics*, 2(3):96–128.

Bentolila, S., J., D. J., and F., J. J. (2020). Dual Labor Markets Revisited. *Oxford Research Encyclopedia of Economics and Finance*.

Blanchard, O. and Landier, A. (2002). The Perverse Effects of Partial Labour Market Reform: Fixed-Term Contracts in France. *The Economic Journal*, 112(480):F214–F244.

Boeri, T. (2011). Institutional Reforms and Dualism in European Labor Markets. In Card, D. and Ashenfelter, O., editors, *Handbook of Labor Economics*, volume 4, pages 1173–1236. Elsevier, Amsterdam: North-Holand.

Bonhomme, S. and Hospido, L. (2017). The Cycle of Earnings Inequality: Evidence from Spanish Social Security data. *The Economic Journal*, 127(603):1244–1278.

Booth, A. L., Francesconi, M., and Frank, J. (2002). Temporary Jobs: Stepping Stones or Dead Ends? *The Economic Journal*, 112(480):F189–F213.

Bratti, M., Conti, M., and Sulis, G. (2021). Employment Protection and Firm-Provided Training in Dual Labour Markets. *Labour Economics*, 69:101972.

Cabrales, A., Dolado, J. J., and Mora, R. (2017). Dual Employment Protection and (lack of) On-the-Job Training: PIAAC Evidence for Spain and Other European Countries. *SERIEs*, 8(4):345–371.

Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2008). Bootstrap-Based Improvements for Inference with Clustered Errors. *The Review of Economics and Statistics*, 90(3):414–427.

Card, D., Heining, J., and Kline, P. (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *Quarterly Journal of Economics*, 128(3):967–1015.

Crawford, V. P. (1988). Long-Term Relationships Governed by Short-Term Contracts. *The American Economic Review*, 78(3):485–499.

de Graaf-Zijl, M., Van den Berg, G. J., and Heyma, A. (2011). Stepping Stones for the Unemployed: The Effect of Temporary Jobs on the Duration until (Regular) Work. *Journal of Population Economics*, 24(1):107–139.

de la Rica, S. (2004). Wage Gaps Between Workers with Indefinite and Fixed-term Contracts: The Impact of Firm and Occupational Segregation. *Moneda y Credito*, 219(1):43–69.

de la Roca, J. and Puga, D. (2017). Learning by Working in Big Cities. *The Review of Economic Studies*, 84(1):106–142.

Dolado, J. J., Ortigueira, S., and Stucchi, R. (2016). Does Dual Employment Protection Affect TFP? Evidence from Spanish Manufacturing Firms. *SERIEs*, 7(4):421–459.

Dustmann, C., Ludsteck, J., and Schoenberg, U. (2009). Revisiting the German Wage Structure. *Quarterly Journal of Economics*, 124(2):843–881.

Felgueroso, F., García-Pérez, J. I., Jansen, M., and Troncoso-Ponce, D. (2018). The Surge in Short-Duration Contracts in Spain. *De Economist*, 166(4):503–534.

Ferreira, M., de Grip, A., and van der Velden, R. (2018). Does Informal Learning at Work Differ Between Temporary and Permanent Workers? Evidence from 20 OECD Countries. *Labour Economics*, 55:18–40.

Filomena, M., Picchio, M., et al. (2021). Are Temporary Jobs Stepping Stones or Dead Ends? A Meta-Analytical Review of the Literature. *IZA DP No. 14367*.

García-Pérez, J. I., Marinescu, I., and Vall Castello, J. (2019). Can Fixed-term Contracts Put Low Skilled Youth on a Better Career Path? Evidence from Spain. *The Economic Journal*, 129(620):1693–1730.

Guvenen, F., Karahan, F., Ozkan, S., and Song, J. (2017). Heterogeneous Scarring Effects of Full-Year Nonemployment. *American Economic Review*, 107(5):369–73.

Heckman, J. J., Lochner, L. J., and Todd, P. E. (2006). Earnings Functions, Rates of Return and Treatment Effects: The Mincer Equation and Beyond. volume 1, pages 307–458. Elsevier, Amsterdam: North-Holand.

Jarosch, G. (2021). Searching for Job Security and the Consequences of Job Loss. *NBER WP No.28481*.

Jarosch, G., Oberfield, E., and Rossi-Hansberg, E. (2021). Learning From Coworkers. *Econometrica*, 89(2):647–676.

Kahn, L. M. (2016). The Structure of the Permanent Job Wage Premium: Evidence from Europe. *Industrial Relations: A Journal of Economy and Society*, 55(1):149–178.

Laß, I. and Wooden, M. (2019). The Structure of the Wage Gap for Temporary Workers: Evidence from Australian Panel Data. *British Journal of Industrial Relations*, 57(3):453–478.

Mertens, A., Gash, V., and McGinnity, F. (2007). The Cost of Flexibility at the Margin. Comparing the Wage Penalty for Fixed-term Contracts in Germany and Spain using Quantile Regression. *LABOUR*, 21(4-5):637–666.

Mincer, J. (1974). Schooling, Experience, and Earnings. . *Human Behavior & Social Institutions No. 2.*

Pesola, H. (2011). Labour Mobility and Returns to Experience in Foreign Firms. *The Scandinavian Journal of Economics*, 113(3):637–664.

Poulissen, D., De Grip, A., Fouarge, D., and Künn-Nelen, A. (2021). Employers' Willingness to Invest in the Training of Temporary Workers: A Discrete Choice Experiment. *IZA DP No. 14395.*

Sanchez, R. and Toharia, L. (2000). Temporary Workers and Productivity: The Case of Spain. *Applied Economics*, 32(5):583–591.

ter Weel, B. (2018). The Rise of Temporary Work in Europe. *De Economist*, 166(4):397–401.

A Supplementary Tables and Figures

Table A.1: Descriptive Statistics

	Mean	Std. Dev
Female	0.523	-
College	0.396	-
Age at Entry	22.30	3.16
Wage at Entry	39.51	22.59
Days Worked at Entry	189.56	105.18
under OEC	33.71	85.48
under FTC	155.85	106.45
Years in the Labor Market	10.50	4.53
Experience (yrs)	5.82	4.49
under OEC	3.22	3.87
under FTC	2.60	2.56
Annual Wage Growth	0.065	0.172
Workers		242,774
Worker-Year Obs.		1,954,097

Notes: Entry refers to the first year of employment after the predicted year of graduation. Accumulated experience refers to the last individual observation. Years in the labor market refers to the average amount of time we observe workers employed in our sample. Experience is measured using daily information and transformed into years. Annual wage growth corresponds to year-on-year wage growth averaged over all observations. Wages are in 2018 euros.

Table A.2: Robustness to Income Measure: Returns to Experience Accumulated under Different Contracts

|	Censored	Tax Data	Pooled Income
Experience OEC	0.0398***	0.0474***	0.0495***
	(0.0004)	(0.0006)	(0.0005)
Experience FTC	0.0370***	0.0410***	0.0439***
	(0.0006)	(0.0007)	(0.0006)
Observations	1,954,097	1,508,948	1,954,097
R-squared	0.3112	0.2306	0.2685

Notes: Experience is measured in days and then it is transformed into years. OEC and FTC stand for experience acquired under open-ended and fixed-term contracts, respectively. Censored specification uses original labor income without correcting for top-coding. Tax data uses information on income coming from tax records for the period 2005-2018. Pooled income consider as measure of daily wages income earned from *all* employers in a given year divided by total days worked in such year. All specifications control for the same variables as the fixed effect panel data model estimates in Column (4) in Table 1. Standard errors clustered at the individual level in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The R-squared reported is within workers.

Table A.3: Robustness to Life-Cycle Control: Returns to Experience Accumulated under Different Contracts

|	Cubic Potential Exp.	Excl. Potential Exp	Age Effects
	(1)	(2)	(3)
Experience OEC	0.0513***	0.0456***	0.0481***
	(0.0005)	(0.0005)	(0.0005)
Experience FTC	0.0432***	0.0393***	0.0414***
	(0.0006)	(0.0006)	(0.0006)
Observations	1,954,097	1,954,097	1,954,097
R-squared	0.3152	0.3080	0.3089

Notes: Experience is measured in days and then it is transformed into years. OEC and FTC stand for experience acquired under open-ended and fixed-term contracts, respectively. Potential experience stands for number of years after labor market entry. All specifications control for the same variables as the fixed effect panel data model estimates in Column (4) in Table 1 except for potential experience fixed effects. Column (1) controls parametrically for potential experience but includes only the squared and cubic terms of potential experience, as the linear term is not identified in the presence of year and individual fixed effects. Column (2) does not include any control for life-cycle differences. Column (3) includes as control fixed effects for age-categories. Standard errors clustered at the individual level in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The R-squared reported is within workers.

Figure A.1: Robustness to Non-Parametric Experience: Returns to Experience Accumulated under Different Contracts
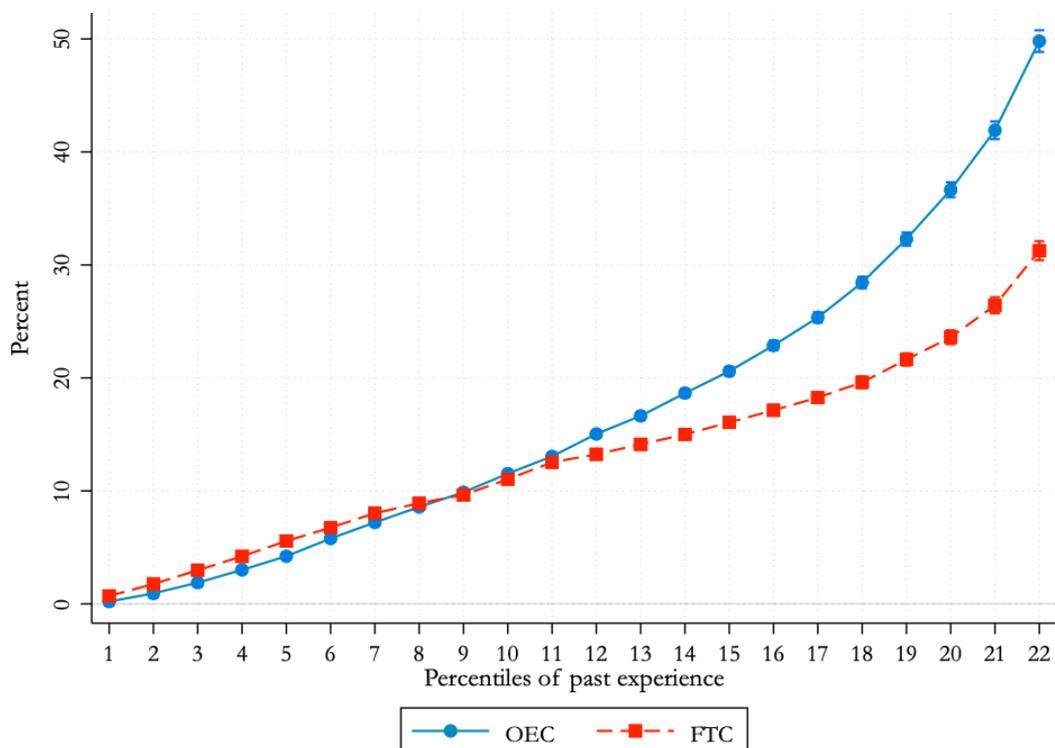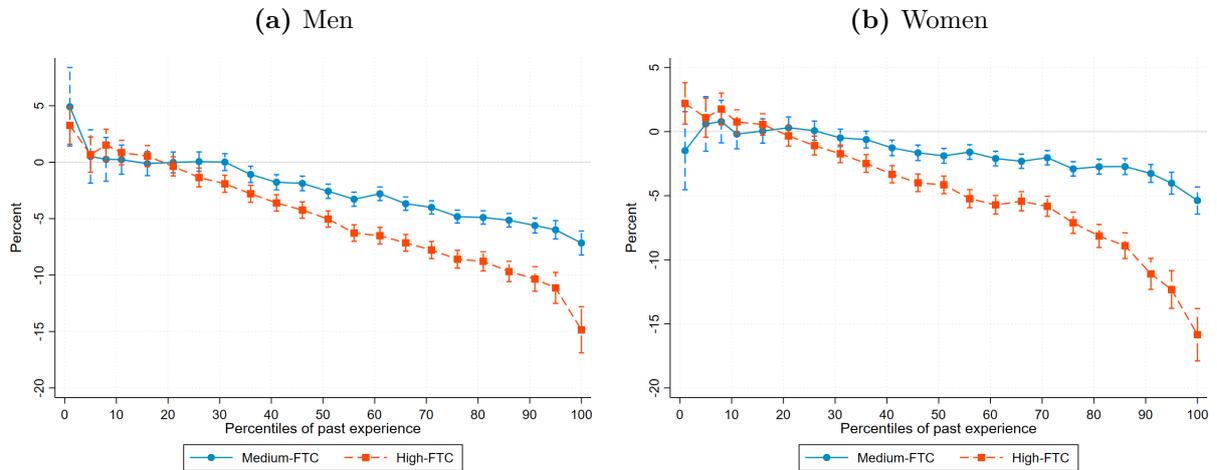

Notes: Estimates ($\times 100$) and 95% confidence intervals of return to experience in fixed-term (FTC) and open-ended (OEC) contracts. Standard errors are clustered at the individual level. Experience is measured in days, transformed into years, and then discretized into 22 percentiles. The model controls for the same variables as the fixed effect panel data model in Column (4) in Table 1.

Figure A.2: Robustness to Thresholds: Scarring Effects of Temporary Employment
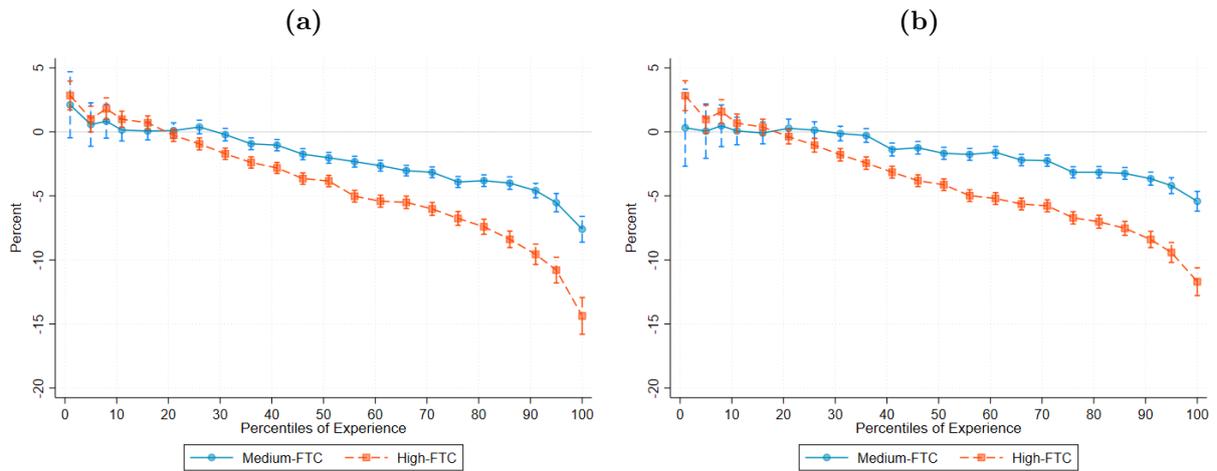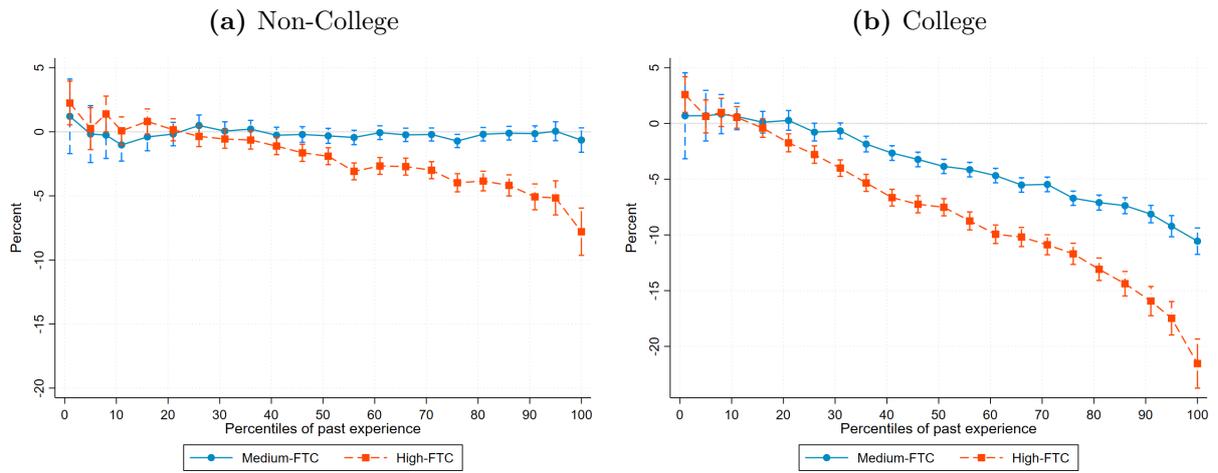
(a)

(b)

Notes: Estimates ($\times 100$) and 95% confidence intervals of the scarring effects of temporary employment, $\beta_{2(q)}$ and $\beta_{3(q)}$, from equation 9. Standard errors are clustered at the individual level. Medium-FTC (High-FTC) incidence refers to individuals whose actual experience on a temporary contract relative to overall actual experience is in Panel (a) between 0.5 and 0.9 (above 0.9) and in Panel (b) between 0.3 and 0.6 (above 0.6).

Figure A.3: Scarring Effects of Temporary Employment by Gender

(a) Men

(b) Women

Notes: Estimates ($\times 100$) and 95% confidence intervals of the scarring effects of temporary employment, $\beta_{2(q)}$ and $\beta_{3(q)}$, from equation 9 estimated separately by gender. Standard errors are clustered at the individual level. Medium-FTC (High-FTC) incidence refers to individuals whose actual experience on a temporary contract relative to overall actual experience is between 0.3 and 0.9 (above 0.9).

Figure A.4: Scarring Effects of Temporary Employment by Education Level

(a) Non-College   **(b)** College

Notes: Estimates ($\times 100$) and 95% confidence intervals of the scarring effects of temporary employment, $\beta_{2(q)}$ and $\beta_{3(q)}$, from equation 9 estimated separately by education level. Standard errors are clustered at the individual level. Medium-FTC (High-FTC) incidence refers to individuals whose actual experience on a temporary contract relative to overall actual experience is between 0.3 and 0.9 (above 0.9).

B   Censoring Correction

The MCVL reports data on monthly labor income from Social Security contribution, which are either bottom or top-coded. In the data, around 13 percent of the log real daily wages of the worker-month observations are top-coded.[16]

Following other studies that face censored earnings in administrative data (Dustmann et al., 2009; Card et al., 2013; Bonhomme and Hospido, 2017), we correct the upper tail by fitting cell-by-cell Tobit models to log real daily wages separately by gender. Each cell, c, is defined according to occupational groups (3 categories), age groups (5 categories), and years (39) for a total of 2×450 cells. Consistent with a vast literature that finds that log-normality provides a reasonable approximation to empirical wage distributions, within each cell, log-daily wages are assumed to follow a Gaussian distribution with cell-specific mean and variance, i.e. $log\ w \sim N(X\beta_c, \sigma_c^2)$.[17]

The parameters of interest are estimated within each cell by maximum likelihood. Denoting Φ the standard normal cdf, the cell-specific maximum likelihood takes the following form (up to an additive constant).

$$\sum_{cens_{it}=0} \left[-\tfrac{1}{2} ln\ \sigma_c^2 - \tfrac{1}{2\sigma_c^2}(ln(w_{ijt}) - X_{it}\beta_c)^2 \right]\ +\ \sum_{cens_{ijt}=1} ln\left(1 - \Phi\left(\tfrac{ln(\bar{w}) - X_{ijt}\beta_c}{\sigma_c} \right) \right)$$

where w_{it} represents real log daily wages of individual i in plant j in moment t (a worker-month pair), $\bar{w}$ is the maximum cap, $cens_{ijt} = 1$ if the observation is top-coded. X_{ijt} is a set of controls such as age, categorical variables for full-time jobs, sector of activity (10), workplace location (50), firm age (3), and monthly dummies (12). Following Card et al. (2013), we also include individual-specific components of the wages using the mean log daily wages in other months, fraction of censored wages in other months, and a dummy for individuals observed only once as additional controls. For individuals who are only observed once, we set the mean log daily wages to the sample mean, and the fraction of censored wages to the share of censored earnings in the sample.

After the estimation, we impute an uncensored value for each censored observation

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[16]Less than 8 percent of the observations are bottom-coded. However, we do not correct the lower tail due to the existence of a national minimum wage.

[17]The choice of the distribution is important and a natural concern is that the results may differ depending on the technique. In this sense, Dustmann et al. (2009) offer an extensive robustness analysis in which they evaluate four different distributional assumptions, and conclude that the results are similar to different specifications. Similarly, Bonhomme and Hospido (2017) use the MCVL to compare the performance of the cell-by-cell Tobit model and a linear quantile censoring correction method with respect to non-censored earnings coming from tax records, and find that the fit is superior with the Tobit model.

using the maximum likelihood estimates of each Tobit model. Specifically, we replace censored observation by the sum of the predicted wages and a random component, drawn from a normal distribution with mean zero and cell-specific variance. The imputation rule is:

$$lnw_{ijt} = X_{ijt}\hat{\beta}_c \; + \; \hat{\sigma}_c\,\Phi^{-1}\left[\Phi\left(\frac{ln\,\bar{w}-X_{ijt}\hat{\beta}_c}{\hat{\sigma}_c}\right) + u_{ijt}\times\left(1-\Phi\left(\frac{ln\,\bar{w}-X_{ijt}\hat{\beta}_c}{\hat{\sigma}_c}\right)\right)\right]$$

where $(\hat{\beta}_c,\hat{\sigma}_c)$ are the maximum likelihood estimates of each cell, Φ denotes the standard normal cdf, and u represents a random draw from the uniform distribution, $U[0,1]$.

Table C.1: Censored and imputed wage distributions

Percentiles	Censored	Imputed
5th	3.00	3.00
10th	3.33	3.33
25th	3.70	3.70
50th	4.04	4.04
75th	4.43	4.45
90th	4.74	5.17
95th	4.78	5.68

Notes: Wages refer to log real daily wages earned by workers in a given employer each month. Moments of the the log daily wage distribution are computed over month-worker-firm observations (93,407,145).

C Variables Definition

Birth date. Obtained from personal files coming from the Spanish Residents registry. We select this information from the most recent wave and, if there is any inconsistency, we choose the most common value over the waves for which it is available.

Education. Retrieved from the Spanish Residents registry up to 2009, and from 2009 thereafter the Ministry of Education directly reports individuals' educational attainment to the National Statistical Office and this information is used to update the corresponding records in the Residence registry. Therefore, the educational attainment is imputed backwards whenever it is possible, i.e. when a worker is observed in the MCVL post-2009. In the imputation, we assigned 25 years as the minimum age to recover values related to university education.[18]

Gender. Obtained from the Spanish Residence registry. We select this information from the most recent wave and, if there is any inconsistency, we choose the mode over the waves in which it is available.

Nationality. Obtained from Spanish Residents registry. The variable reports the link between the individual and Spain in terms of legal rights and duties. This variable allows to distinguish between individuals with Spanish nationality (N00 code) and other worldwide nationalities.

Labor market entry. To define labor market entry, we exploit information on education attainment and compute predicted graduation year of each individual. Specifically, education-specific graduation years are assigned as the years when high-school drop-outs turn 16, people with high-school degrees turn 18, and college graduates turn 23. We track workers after their predicted graduation year to compute time employed and out-of-work.

Experience. Defined as the time actually worked relative to overall time after labor market entry. We compute actual working days using information on all the spells available for each worker in the MCVL since labor market entry. Specifically, at each year t, we count the exact number of days worked and compute our measure of experience as the

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[18]The age threshold is the average graduation age for a Bachelor's degree in Spain: https://www.oecd.org/education/education-at-a-glance-19991487.htm

share of time actually worked in the past relative to the potential time that an individual could have worked since labor market entry.

Labor income. The MCVL reports labor income from two different sources: Social Security contribution basis and income tax records. Contribution bases capture gross monthly labor earnings plus one-twelfth of year bonuses.[19] Earnings are bottom and top-coded. The minimum and maximum caps vary by Social Security regime and contribution group, and they are adjusted each year according to the evolution of the minimum wage and inflation rate. The data is supplemented with information provided by the Fiscal Authorities on the total wages that employers pay to employees on an annual basis. The advantage of this measure is that it is not censored. However, fiscal information is only included from 2005 onwards and excludes Basque Country and Navarra. Our main analysis relies on labor income coming from Social Security contributions and we correct top-censored earnings fitting cell-by-cell Tobit models to log real daily wages (see Appendix B).

Employment status. An individual is considered to be employed in a given year if annual income is at least equal to one quarter of full-time work at half of the minimum wage.

Contract type. The MCVL contains a long list of contract types (over 100) that are summarized in two broad categories, according to its permanent or temporary nature. Permanent contracts include regular permanent contracts (*contrato inde nido jo*) and intermittent (seasonal) permanent contracts (*inde nido jo-discontinuo*). Temporary contracts include specific project or service contracts (*temporal por obra o servicio*), temporary increase in workload (*eventual de produccion*), and substitution contracts (*interinidad o relevo*).

Occupation category. Based on Social Security contribution group. These groups indicate a level in a ranking determined by the worker's contribution to the Social Security system, which is determined by both the education level required for the specific job and the complexity of the task. The MCVL contains 10 different contribution groups that are aggregated according to similarities in skill requirements. High-Skill: Group 1 (engineers,

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[19]Exceptions include extra hours, travel and other expenses, and death or dismissal compensations.

college, senior managers —in Spanish *ingenieros, licenciados y alta direccion*), Group 2 (technicians —*ingenieros tecnicos, peritos y ayudantes*), and Group 3 (administrative managers —*jefes administrativos y de taller*). Medium-Skill: Group 4 (assistants —*ayudantes no titulados*) and Group 5-7 (administrative workers —*o ciales administrativos* (5), *subalternos* (6) and *auxiliares administrativos* (7)). Low-Skill: Group 8-10: (manual workers —*o ciales de primera y segunda* (8), *o ciales de tercera y especialistas* (9) y *mayores de 18 aнos no cuali cados* (10)).

Establishment. Defined by its Social Security contribution account (*codigo de cuenta de cotizacion*). Each firm is mandated to have as many accounts as regimes, provinces, and relation types with which it operates. The contribution accounts are assigned by the Social Security administration, and they are fixed and unique for each treble province-Social Security regime-type of employment relation.[20] Thus, contribution accounts can be thought of as establishments.

Establishment creation date. Date when the first employee was registered in the contribution account. We rely on this date as a proxy for the workplace creation date to classify employers into age bins.

Establishment size. Number of employees working in the establishment at the moment of data extraction. Unfortunately, this variable is missing before 2005. For the years in which the variable is missing, we assigned the average size observed for that establishment from 2005 onwards. In the case of establishments not observed after 2005, we assigned a value of zero.[21]

Establishment location. The municipality in which the establishment conducts its activity if above 40,000 inhabitants, or the province for smaller municipalities (*domicilio de actividad de la cuenta de cotizacion*). Based on that, we group all locations into the 50 Spanish provinces.

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[20]According to the Social Security administration, around 85 percent of the firms are single unit organizations, i.e. there have just one contribution account per firm. Each firm has typically one account for each treble province-Social Security regime-type of employment relation.

[21]We tested our results by including a dummy variable in our regressions to identify firms not observed after 2004. However, our main results are not affected, so we avoid including such an indicator.

Sector of activity. The MCVL provides information on the main sector of activity at a three-digit level (*actividad economica de la cuenta de cotizacion, CNAE*). Due to a change in the classification in 2009, the MCVL contains CNAE93 and CNAE09 for all establishments observed in business from 2009 onwards, but only CNAE93 for those which stop their activity before. We rely on the CNAE09 classification when available, and CNAE93 otherwise. Then, we aggregate the three-digit industry information into 10 categories corresponding to primary sector, manufacturing, utilities, construction, trade and transport, accommodation and restaurants, business services, public sector, private health institutions, education, and other services.