Labour Economics 17 (2010) 632–642

Contents lists available at ScienceDirect

Labour Economics

journal homepage: www.elsevier.com/locate/labeco

Labor market flexibility and poverty dynamics

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ARTICLE INFO

Article history:
Received 8 April 2009
Received in revised form 2 December 2009
Accepted 8 January 2010
Available online 28 January 2010

Keywords:
Temporary employment
Poverty
Fixed-term contracts
Feedback effects
State dependence
Spain

ABSTRACT

The past two decades have witnessed a rapid growth in flexible work arrangements that, in some instances, could expose workers to a higher poverty risk via limited job stability, few advancement opportunities, and low wages. Nowhere in the world has this increase in flexible work arrangements being more evident than in Spain, where about a third of the wage and salary workforce holds fixed-term contracts. Using Spanish panel data and maximum-likelihood binary models that account for state dependence and unobserved heterogeneity, we examine the poverty implications of past and present temporary employment. Our findings suggest that fixed-term contracts are linked to a greater poverty exposure among women and older men relative to open-ended contracts. Furthermore, this greater poverty exposure can last several years due to feedback effects operating via job instability or via the transition to work statuses characterized by higher poverty hazards. Finally, the adverse impact of temporary employment is linked to the short duration of some contracts, thus signaling the importance of work attachment.

1. Introduction

One of the major labor market developments of the past decades has been the rapid growth of jobs lacking an explicit or implicit contract for long-term employment. The increased prevalence of these fixed-term jobs has delivered some benefits, such as maintaining a low unemployment rate,[2] providing a second household income, or serving as a stepping-stone to better paid jobs for many individuals.

However, these benefits have not come without costs. First, workers in temporary work arrangements often endure limited job stability, experience fewer opportunities for advancement, and earn lower wages than employees with open-ended contracts in so-called permanent jobs. Second, temporary employees suffer frequent unemployment spells due to the short-term nature of their work arrangements, which result in sharp income shortfalls endangering their economic self-sufficiency. These factors enhance the poverty risk of temporary workers contemporaneously and in the near future. While the increasing availability of longitudinal surveys has fostered a series of poverty studies that examine poverty dynamics among workers,[3] very few studies have directly assessed the link between temporary employment and poverty due to: (a) the econometric challenges involving such an exercise, and (b) the weak link in family-oriented southern European countries between individual and household income. This is surprising considering the prevalence of temporary employment in some economies and the poor working conditions often associated to these jobs.[4]

In this paper, we examine the link between temporary work and poverty using Spanish data from the European Community Household Panel (ECHP). The Spanish labor market constitutes a remarkable case with approximately one third of its workforce employed in temporary jobs. Additionally, Spain is one of the European countries with higher

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2 For instance, in the U.S., (Katz and Krueger, 1999) have estimated that the unemployment rate would be 14% higher if not for the expansion of temp agencies, which is estimated to account for approximately 10% of the job growth in the 1990s (Wessel, 2001).

3 For instance, in the U.S. (Hill, 1981; Plotnick, 1983; Duncan, 1984; Bane and Ellwood, 1986; Sawhill, 1988; Gottschalk and Moffitt, 1994; Hoynes and MaCurdy, 1994; Huff Stevens, 1994), and Duncan et al. (1996), among other ones, use the Panel Study of Income Dynamics (PSID). Other authors, such as (Blank and Ruggles, 1994) and Klawitter et al. (2000), use the Survey of Income and Program Participation (SIPP) and the 1979 National Longitudinal Survey of Youth, respectively. For Spain, see (Cantó, 1996; Cantó, 2002).

4 As we shall discuss in what follows, the exceptions are studies focusing on the U.S. and, often, on specific types of fixed-term contracts. In particular, Heinrich et al. (2005) examine the link between temporary help agency employment and welfare dependency, and (Bansak and Amuedo-Dorantes, 2003) analyze the relationship between various forms of contingent employment and poverty.

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doi:10.1016/j.labeco.2010.01.004

levels of low-wage employment[5] and structural unemployment rates. Via frequent unemployment spells owing to the limited duration of their contracts, temporary workers are likely to endure a higher poverty risk. Using maximum-likelihood limited dependent variable models that account for state dependence, individual heterogeneity correlated with the regressors and feedback effects, we examine the link between past and present temporary work of varying duration and the likelihood of being poor. The distinction between contemporaneous and future links of temporary employment to poverty is important since policy implications may differ depending on whether the welfare effects associated to fixed-term contracts are long lasting.

We also distinguish between the direct link between poverty and past temporary employment (i.e. controlling for *present* work status) and the indirect link between poverty and past temporary employment via feedback effects. In particular, we relax the unrealistic assumption of temporary employment being exogenous and, instead, allow for any indirect or feedback effects from past temporary employment on poverty operating via job instability or via the transition to work statuses characterized by higher poverty hazards.

Finally, we investigate possible differences in the association between poverty and temporary employment by gender, age, and the duration of the fixed-term contract held by the employee. This analysis is of special interest given the diverse implications of short-term versus longer term temporary work depending on the employee's gender and age.[6]

In sum, this project provides insight into whether temporary employment strengthens or, rather, dampens temporary workers' economic opportunities contemporaneously and in the near future relative to permanent employment. When doing so, we account for the endogeneity of the current work status emerging: (a) via unobserved individual level heterogeneity contemporaneously, and (b) via feedback effects referred to past temporary work. Despite these controls, we cautiously interpret our results as evidence of a strong correlation or link between temporary work and poverty rather than as unequivocal evidence of a causal relationship between the two given that there may be additional sources of endogeneity.[7] We find that temporary employment is linked to a higher contemporaneous poverty risk among women and older men relative to permanent employment. This link seems to be driven by the harmful impact of short lived fixed-term contracts, thus signaling the importance of work attachment. Additionally, past temporary employment adds to men's and women's poverty risk via significant feedback effects. As such, while lower salaries and worse working conditions endured by temporary workers may contribute to their contemporaneous poverty risk, it is the inherent lack of job stability endured by past temporary employees that seems to reinforce their future poverty risk. These findings underscore the value of longer lived work contracts and policies aimed at facilitating the transition from fixed-term to open-ended contracts in fighting poverty.

2. Temporary employment in Spain

2.1. The Spanish labor market

Following Franco's regime, the Spanish economic infrastructure was obsolete and its system of industrial relations was characterized by strong government intervention and centralized bargaining that protected lifetime jobs (Jimeno and Toharia, 1993). The need for flexibility and modernization of labor market institutions and employment contracts became evident. The Workers' Statute (1980) and its 1984 reform accommodated the needs of a changing labor market and an economy in recession by deregulating the use of temporary work contracts by firms. In particular, the new employment regulation introduced an array of work relationships that implied a complete breakthrough from the highly paternalistic employment regulation contained in the 1976 Law of Labor Relations, the Spanish Jurisprudence, and various labor ordinances protecting lifetime jobs. Fixed-term contracts offered firms the possibility to hire and dismiss workers at a much lower cost compared to open-ended contracts. In addition to the new types of work contracts, the Workers' Statute regulated working conditions for temporary and permanent workers requiring equal wages for the same type of job.[8] Nonetheless, despite the legislation's mandate to pay equal wages, temporary workers have been found to earn lower wages than their counterparts in more stable jobs (Jimeno and Toharia, 1993; Bentolila and Dolado, 1994).

As pointed out by Dolado et al. (2002), temporary employment quickly grew from less than 10% in the early 1980s to approximately 30% of the workforce by the second half of the decade. In response to its rapid growth, several reforms were implemented during the 1990s and in 2001 aimed at reducing firms' extensive use of fixed-term contracts. However, temporary employment has shown considerable resilience, only declining from 35% in the mid 1990s to approximately one third of the Spanish workforce as of today.

2.2. Temporary employment and poverty

According to human capital theory, limited on-the-job training and frequent unemployment spells characteristic of fixed-term contracts impede the continuous accumulation of work skills and, instead, favor the depreciation of acquired human capital.[9] Coupled with commonly lower wages and frequent ineligibility for unemployment benefits, these factors may contribute to temporary workers' contemporaneous and future poverty risk. Moreover, the differential treatment that the early regulation of temporary and permanent employment granted to workers in each of these work arrangements, together with unions' clout and traditionally high unemployment rates, favored the emergence of a segment of rationed well-paid permanent jobs and another segment of contingent jobs with worse working conditions (Bentolila and Dolado, 1994). According to the theory on dual labor markets, the limited mobility between these two labor market segments may further favor the involuntary confinement of temporary workers into jobs with lower wages and poorer working conditions; hence, enhancing their future poverty risk. Finally, in the case of women, interrupted work patterns may also foster statistical discrimination by employers, impairing

[5] See the report "Working Poor in the European Union" from the European Foundation for the Improvement of Living and Working Conditions, Luxembourg: Office for Official Publications of the European Communities, (European Foundation for the Improvement of Living and Working Conditions, 2004).

[6] For instance, short-lived contracts are more likely to be representative of precarious work arrangements with a lower level of employee and employer commitment. Yet, the poverty implications of holding short-lived contracts may differ with the worker's age. For example, short-term contracts may not be linked to poverty when held by younger workers as a stepping-stone to better employment. Likewise, as we discuss later on, men and women may use fixed-term contracts with different purposes.

[7] The fact that up to 85% of temporary employment is considered involuntary reinforces our concern regarding the potential endogeneity of the type of work contract held (see the report: "Employment in Europe 2008" from the European Commission, Directorate General for Employment, Social Affairs, and Equal Opportunities. Brussels, (Directorate General for Employment, Social Affairs, and Equal Opportunities, 2008).

[8] The unconstitutionality of paying different wages to workers carrying out the same type of job has been repeated in various occasions by the Supreme Courts, see: TS 13-5-91, RJ 3909, RJ 5483, and RJ 118. Additionally, the Constitutional Courts in TCo 177/1993 have stated that the shorter contract duration is not sufficient to justify a lower rate of pay.

[9] Bartik (1997) finds evidence that welfare recipients in the U.S. who stay longer in the job benefit from more work experience and opportunities for general and firm-specific skills training compared to those who take short-duration temporary jobs.

women's advancement career-wise and, thereby, raising their future poverty risk.[10]

Alternatively, temporary work may provide families with income relief and reduce their poverty risks by facilitating the employment of some household members less attached to the labor market.[11] Additionally, even if it is involuntary,[12] temporary employment may function as a stepping-stone for inexperienced workers, provide a path towards self-reliant employment and reduce their exposure to poverty in the near future relative to dead-end permanent employment.[13] As such, whether fixed-term work raises temporary workers' poverty risk contemporaneously and in the near future remains an empirical question.

2.3. Literature review

While both poverty and temporary employment have been the focus of an extensive body of literature, few studies have examined the link between contingent work and poverty exposure. Some exceptions, although focusing on the U.S. experience, are the study by Bansak and Amuedo-Dorantes (2003) examining the relationship between poverty and a variety of contingent work arrangements using the 1979 National Longitudinal Survey of Youth (NLSY79),[14] the analysis of a Michigan welfare-to-work program by Autor and Houseman (2006), and the studies on contingent work and welfare dependency by Heinrich (2005) and Heinrich et al. (2005) using data on North Carolina and Missouri. Nonetheless, the regulation and magnitude of temporary employment in Spain make the study of any poverty implications of fixed-term employment in this country of special interest.

Focusing on Spain, there are three different strands of literature that shed light on the relationship between poverty and contingent work: (i) Research on poverty determinants, (ii) studies of low wages and poverty, and (iii) research on low wages and temporary employment. Within the first category, Cantó (1996) and Cantó (2002) provides some insight into the determinants of poverty incidence and duration, as is the case with the part-time work status of the household head.[15] Cantó (2002) also finds that there is evidence of poverty state dependence for as long as fifteen months. However, she does not address the link between poverty and contingent work. In a related study, Poggi (2007) examines the persistence of social exclusion using the Spanish data from the ECHP.[16] She estimates a dynamic random effects logit model following Wooldridge (2000). By using time-invariant covariates, she circumvents the assumption of exogenous regressors and also finds a significant degree of state dependence. However, the use of time-invariant regressors rules out the possibility of assessing the existence of any feedback effects of past work statuses on poverty via job instability or via the transition to work statuses with greater poverty hazards.

Other studies have focused on the incidence of poverty among low-wage workers. While there are no studies exclusively focusing on Spain, Marx and Verbist (1999) use European data to show that poverty rates for the working age population tend to be consistently higher in countries where low-wage work is more prevalent.[17]

Finally, a third strand of research has examined the link between low wages and temporary employment. For instance, Jimeno and Toharia (1993) use a cross-section of temporary and permanent workers and find that temporary workers earn between 7% and 11% less than permanent workers. Bentolila and Dolado (1994) estimate that the widespread use of temporary contracts accounts for the growing wage gap between “perms” and “temps.” More recently, Amuedo-Dorantes and Serrano-Padial (2007) examine the effect of the duration of temporary employment on workers' current and future wages. They find that, while temporary workers earn significantly less than their permanent counterparts contemporaneously, their wages quickly improve if they are able to keep their jobs.

In sum, the existing research suggests that, relative to permanent employment, fixed-term work may increase temporary workers' exposure to poverty through low wages and high turnover rates. However, fixed-term jobs could help lower temporary workers' poverty likelihood if they provide inexperienced and unskilled workers with a stepping-stone to more promising placements or if they help individuals earn a second household income. In what follows, we examine which of these two predicted effects is supported empirically by the data with an analysis of the poverty implications of past and present temporary employment that accounts for individual heterogeneity, poverty state dependence and feedback effects.

3. Data and descriptive evidence

We use Spanish data from eight consecutive waves (1994–2001 inclusive) from the European Community Household Panel (ECHP) – a longitudinal survey started by the European Union member countries in 1994.[18] The survey collects information from approximately 70,000 households, of which 8000 reside in Spain.

In addition to household and individual demographic and work-related characteristics, the dataset collects information on the labor force status and earnings of each individual when employed. The survey questionnaire allows us to categorize respondents into one of the following groups: out of the labor force, unemployed, self-employed, and employed as wage and salary workers. Within the last category, we distinguish temporary workers with fixed-term contracts, which are the focus of our analysis, from permanent workers with open-ended contracts and from *other* workers. *Other* workers can be: (1) employees working less than 15 h/week for whom we lack information on the type of work contract held, or (2) employees working 15 or more hours/week without a contract or with an apprenticeship, a training contract or a similar type of work arrangement. As such, all respondents fall into one of the following six categories: permanent, temporary, *other*, self-employed, unemployed and inactive. When we further distinguish

[10] The higher labor market withdrawal rate exhibited by women relative to men may foster employers' beliefs of female candidates as being less committed to their jobs.

[11] Gradín and Cantó (2009) find that the share of unemployed household members increases the risk of poverty in all households, suggesting that any employment may be better than no employment. Yet, that seems to be only true with respect to the household head, as they also find that the share of household members with fixed-term contracts is also positively related to a higher risk of poverty among households with children.

[12] Even if the temporary work assignment is involuntary, it may be used as a stepping-stone to a more desirable job in the near future.

[13] A series of studies have confirmed that temporary employment can, at times, serve as a stepping-stone in Spain (see Amuedo-Dorantes and Serrano-Padial, 2007) as well as in other countries (e.g. (Booth et al., 2002) for the U.K., (Kvasnicka, 2008) for Germany, (Picchio, 2008) for Italy, and (Tunny and Mangan, 2004) for Queensland). Generally, these findings, despite accounting for the worker's educational attainment, refer to all workers.

[14] Bansak and Amuedo-Dorantes (2003) investigate how past employment in alternative types of contingent jobs may affect the likelihood of living in poverty, although without accounting for individual heterogeneity. Using NLSY79 data, they find that the type of work contract does not, by itself, increase the individual's likelihood of life in poverty in the near future.

[15] Cantó (1996) estimates logit regressions with poverty duration dummies. Cantó (2002) uses n-order logit Markov model of poverty and non-poverty spells to jointly estimate poverty exit and re-entry determinants.

[16] She defines social exclusion as a process where individuals or groups fully or partially excluded from social, economic and cultural networks. Therefore, social exclusion is a process leading to a state of multiple functioning deprivations.

[17] They use 1989–94 data from the U.S., Canada, Europe and Australia.

[18] The ECHP was discontinued in 2001 and substituted by the European Union Statistics on Income and Living Conditions survey (EU-SILC). However, we only have Spanish data in the EU-SILC for the period 2004 through 2007 (i.e. four years), whereas the ECHP allows us to work with eight years of data. Because the households cannot be linked across both surveys and the incidence of temporary work does not appear to have significantly changed since the mid 1980s, we use the ECHP to improve on the efficiency of our estimates.

Table 1
Summary statistics.

Variable	All mean (s.d.)	Non-poor mean (s.d.)	Poor: All mean (s.d.)	Poor: Men mean (s.d.)	Poor: Women mean (s.d.)
Age	38.25 (0.077)	38.46 (0.093)	37.95 (0.186)	37.92 (0.278)	37.97 (0.2502)
Male	49.76%	50.09%	46.81%		
Married	55.79%	56.30%	59.06%	59.83%	58.37%
Family size	4.24 (0.011)	4.21 (0.014)	4.42 (0.026)	4.54 (0.037)	4.31 (0.036)
Education					
Middle school	24.60%	23.68%	28.01%	27.59%	28.37%
Occupational training	12.48%	12.87%	8.04%	9.03%	7.18%
High school	14.11%	15.52%	8.73%	8.24%	9.15%
College	14.31%	15.89%	3.47%	2.82%	4.03%
Work status					
Permanent worker	24.43%	27.41%	5.57%	10.20%	1.49%
Temporary worker	10.96%	11.31%	7.82%	12.15%	4.00%
Other worker	4.24%	3.85%	5.37%	5.35%	5.38%
Self-employed/family business	11.42%	10.99%	12.85%	19.74%	6.78%
Unemployed	11.34%	9.70%	22.22%	22.86%	21.65%
Out of the labor force	37.62%	36.74%	46.18%	29.69%	60.69%
No. of observations	49,825	40,983	8842	4086	4756

according to the duration of the fixed-term contract held, we consider four categories: workers with up to a 6-month contract, workers with a 7 to 12-month contract, workers with a fixed-term contract lasting over 1 year, and other temporary workers, such as those lacking a written contract.

Table 1 shows the means and standard deviations of the main variables used in the analysis and informs on some of the characteristics of poor and non-poor individuals in the sample.[19,20] Since men and women usually display different labor force participation patterns, we examine them separately. According to the figures in Table 1, poverty displays a higher incidence on women than men. Overall, 18% of individuals are considered poor, with few differences between the poor and the non-poor in terms of age or family size. The main discrepancies between poor and non-poor individuals are found with regards to their educational attainment and work statuses. Non-poor individuals are better-educated and are more likely to be employed than their poor counterparts. Indeed, approximately 47% of poor men work, whereas only 17% of poor women are employed.

Even though working respondents are less likely to live in poverty, temporary employees (focus of our study) endure higher poverty incidence rates than permanent workers. As shown in Table 2, only 4% of permanent workers are considered poor relative to 13% of temporary workers. The incidence of poverty among male temporary workers is even higher (15%) than among women in that work status (10%). Nonetheless, women on temporary jobs have poverty rates five times greater than their permanent counterparts.

The higher incidence of poverty among temporary workers may be less worrisome if income mobility is relatively high. Table 3 displays a one-year poverty transition matrix across work statuses. The main finding that emerges from Table 3 is the existence of relatively high

Table 2
Poverty incidence by work status.

Work status	All	Men	Women
Permanent worker	4.15%	5.38%	1.75%
Temporary worker	12.85%	14.47%	9.89%
Other worker	22.93%	25.37%	21.15%
Self-employed/family business	19.95%	20.08%	19.63%
Unemployed	32.81%	35.47%	30.68%
Out of the labor force	21.14%	20.57%	21.40%
Total	17.58%	16.62%	18.52%

poverty persistence.[21] On one hand, apart from unemployed individuals, poverty entry rates are the largest for non-poor respondents who were self-employed in the past, with 11% of them considered poor a year later. In contrast, only 2% of non-poor permanent workers are poor a year later. Temporary workers fall somewhere in between, enduring poverty entry rates two times greater than permanent workers. Poverty exit rates, on the other hand, range between 62% for permanent employees and 51% for *other* contingent workers. At first sight, permanent and temporary workers exhibit similar poverty exit rates. However, a closer look reveals some interesting differences regarding the mechanism by which these two types of workers escape poverty. Twenty-eight percent of temporary workers escape poverty within the period of one year while still employed in fixed-term jobs. This percentage compares to 42% of permanent workers able to escape poverty over the same time span while still employed on a permanent basis. As such, permanent employment can be more effective at helping workers escape poverty than fixed-term work.

The persistence of poverty among temporary workers may be linked to their limited upward employment mobility.[22] Only 12% of temporary workers living in poverty become employed on a permanent basis a year later. This rate, however, rises to 26% among non-poor temporary workers, pointing to the importance of individual unobserved heterogeneity in explaining poverty. Finally, the persistence of poverty among temporary workers may also be due to the higher transition rate to unemployment endured by fixed-term workers.

Summarizing, preliminary descriptive statistics corroborate the hypothesis that temporary work, as other forms of contingent employment, maybe linked to a greater poverty exposure than permanent employment. In particular, temporary workers display higher poverty incidence rates, higher poverty entry rates, and lower poverty exit rates if still employed on a temporary basis than permanent workers. As a result, temporary workers are likely to endure a higher degree of poverty state dependence in part due to their work status dependence and their high transition rate to unemployment. Because poverty incidence may be explained, to a large extent, by observed and unobserved individual level characteristics associated to the work status held by the worker and by poverty state dependence, we next turn to a more in-depth analysis that accounts for all these factors.

4. Empirical methodology

In assessing the link between past and present temporary work and poverty, we encounter three important econometric problems. First, poverty is likely to show strong state dependence. If we account for unobserved heterogeneity, it is possible to distinguish *true* state dependence from the role played by unobserved individual characteristics. Secondly, since unobserved heterogeneity is likely to be correlated with most explanatory variables, such as work status,

19 Following the poverty definition of EUROSTAT, we deem an individual in a given household as poor if the household *equivalent* income is below the poverty line, set at 0.6 × (*median equivalent income*). Equivalent income is year-specific and equal to the household disposable income divided by the number of equivalent adults according to the modified OECD equivalence scale (*# of equivalent adults* = 1 + 0.5 × (*# of adults* − 1) + 0.3 × (*# of children*)).

20 Income variables in the ECHP refer to income earned during the previous calendar year. Since employment and demographic variables refer to the current year, we define poverty status in period t using income information from period $t+1$.

21 The literature examining income mobility in Spain and other countries is too long to properly address it here. Yet, we would like to note that Spain appears to be somewhere in between other European nations when it comes to income mobility. In particular, Ayala and Sastre (2004) find that Italy and France are the countries with the highest and lowest mobility, respectively.

22 As noted by Ayala and Sastre (2005), employment earnings are one of the income sources most linked to longitudinal income changes.

Table 3
Poverty transition matrix by work status.

Past work status	Present work status													
	Non-poor							Poor						
	Perm	Temp	Other	Self	Unem	OutLF	Total	Perm	Temp	Other	Self	Unem	OutLF	Total
Non-poor														
Permanent worker	0.867	0.045	0.011	0.016	0.016	0.027	98.17%	0.012	0.001	0.001	0.001	0.002	0.001	1.81%
Temporary worker	0.257	0.481	0.057	0.019	0.097	0.042	95.27%	0.005	0.017	0.003	0.003	0.016	0.003	4.73%
Other worker	0.156	0.200	0.239	0.044	0.140	0.132	91.04%	0.006	0.012	0.030	0.004	0.022	0.016	8.95%
Self-employed	0.042	0.026	0.019	0.730	0.019	0.057	89.14%	0.001	0.005	0.002	0.084	0.005	0.012	10.86%
Unemployed	0.060	0.179	0.073	0.042	0.337	0.193	88.47%	0.004	0.010	0.010	0.006	0.056	0.029	11.52%
Out of labor force	0.009	0.028	0.023	0.018	0.065	0.780	92.32%	7.3E-5	0.001	0.002	0.002	0.009	0.063	7.69%
Poor														
Permanent worker	0.424	0.094	0.012	0.032	0.037	0.022	62.01%	0.254	0.044	0.013	0.037	0.014	0.018	38.00%
Temporary worker	0.081	0.278	0.045	0.021	0.117	0.060	60.09%	0.042	0.181	0.034	0.009	0.099	0.035	39.93%
Other worker	0.035	0.116	0.128	0.034	0.117	0.078	50.80%	0.027	0.070	0.106	0.027	0.155	0.106	49.18%
Self-employed	0.022	0.023	0.008	0.483	0.024	0.052	61.28%	0.008	0.016	0.012	0.265	0.035	0.052	38.73%
Unemployed	0.018	0.098	0.034	0.031	0.203	0.102	48.59%	0.007	0.052	0.043	0.020	0.281	0.112	51.41%
Out of labor force	0.007	0.024	0.017	0.016	0.053	0.406	52.27%	0.001	0.009	0.010	0.007	0.060	0.391	47.74%

failure to account for individual heterogeneity is likely to yield inconsistent parameter estimates. Finally, work status itself cannot be treated as strictly exogenous in the presence of state dependence since: (i) past poverty can influence the current work status, and (ii) past work status is likely to indirectly affect the likelihood of being poor via feedback effects operating through job instability and the transition to work statuses with higher poverty hazards.

In order to appropriately address the aforementioned problems, we estimate a nonlinear dynamic panel data model that controls for unobserved heterogeneity, state dependence and feedback effects of predetermined variables, such as past work status. Few analyses do this. One exception is the study of Biewen (2004) on the poverty effects of changes in employment status using German data. He proposes a dynamic random effects probit model following Wooldridge's (2000) framework.[23] Our econometric approach differs from Biewen's (2004) in that it allows for work status to take on multiple values. As such, we are able to more realistically model employment options than when work status is specified as a simple dichotomous variable (*employed/unemployed*).

We estimate our model using the conditional maximum likelihood approach for limited dependent variables proposed by Wooldridge (2000). Alternatively, one could use pooled random effects methods (see Wooldridge, 2002a) or the semi-parametric estimators proposed in Honoré and Lewbel (2002) and Arellano and Carrasco (2003). The pooled random effects methods, like the semi-parametric estimators proposed by Honoré and Lewbel (2002), do not allow us to estimate the feedback effects of past temporary work on poverty. Yet, gauging the poverty risk associated to these indirect effects is important since their magnitude largely exceeds the size of the direct effect of past temporary employment on poverty. Finally, the GMM approach of Arellano and Carrasco (2003) runs into feasibility issues in the presence of large number of regressors, as noted by Biewen (2004). While Wooldridge's correlated random effects framework requires modeling the relationship between unobserved heterogeneity and the regressors, a linear specification saturated with interaction terms will likely capture this relationship provided most of our regressors are binary.[24] Furthermore, the treatment of initial conditions in Wooldridge (2000) avoids the strong identification assumptions used in alternative correlated random effects specifications, e.g. Chay and Hyslop (2000).[25]

4.1. The conditional likelihood

Let y_{it} denote the poverty status of individual $i = 1,\ldots,n$ in period $t = 1,\ldots,T$. We assume that y_{it} is given by the following model:

$$y_{it} = 1\left\{\beta_z z_{it} + \beta_{ws} ws_{it} + \beta_{ws_{-1}} ws_{it-1} + \beta_y Y_{it-1} + c_i + e_{it} \geq 0\right\}, \quad (1)$$

where z_{it} is a vector of strictly exogenous personal and household variables, ws_{it} is a set of (weakly exogenous) work status dummy regressors, and $Y_{it-1} = (y_{it-1}, y_{it-2}, \cdots, y_{it-k})'$ is a vector of k lags of poverty status aimed at capturing state dependence. Finally, c_i and e_{it} represent the unobserved time-invariant individual effect and the idiosyncratic error, respectively. Assuming the cdf of e_{it}, $G(.)$, is symmetric about zero, we have that:

$$P(y_{it} = 1 | z_{it}, ws_{it}, ws_{it-1}, Y_{it-1}, c_i) = G(\beta X_{it} + c_i), \quad (2)$$

where $\beta = \left(\beta_z, \beta_{ws}, \beta_{ws_{-1}}, \beta_y\right)$ and $X_{it} = (z_{it}, ws_{it}, ws_{it-1}, Y_{it-1})'$. Therefore, the conditional density of y_{it} is given by:

$$f(y_{it} | X_{it}, c_i; \beta) = [G(\beta X_{it} + c_i)]^{y_{it}} [1 - G(\beta X_{it} + c_i)]^{(1 - y_{it})}. \quad (3)$$

If $g(.| z_{it}, ws_{it-1}, Y_{it-1}, c_i; \delta)$ is the conditional density of ws_{it}, and we assume that the idiosyncratic error term is serially uncorrelated,[26] we can write the joint density of $((y_{iT}, ws_{iT}), \cdots, (y_{i1}, ws_{i1}))$ conditional on $(Z_{iT}, ws_{i0}, y_{i0}, c_i)$ as:[27]

$$\begin{aligned} &p((y_{iT}, ws_{iT}), \cdots, (y_{i1}, ws_{i1}) | Z_{iT}, ws_{i0}, y_{i0}, c_i; \beta, \delta) \\ &\quad = \prod_{t=1}^{T} f(y_{it} | X_{it}, c_i; \beta) g(ws_{it} | z_{it}, ws_{it-1}, Y_{it-1}, c_i; \delta). \end{aligned} \quad (4)$$

In order to perform maximum-likelihood estimation, we need to obtain a conditional density that does not depend on the unobserved individual effect. Accordingly, Wooldridge (2000) suggests modeling the distribution of the individual effect conditional on the exogenous variables and on the initial conditions $(h(c_i | Z_{iT}, ws_{i0}, y_{i0}; \theta))$ to then

[23] In the context of unemployment dynamics, Stewart (2007) also estimates a bivariate random effects probit with state dependence in which he accounts for feedback between unemployment and low-wage employment.

[24] Additional flexibility is introduced by estimating separate regressions for four different age-gender groups.

[25] Wooldridge (2000) shows that no assumptions on the distribution of initial conditions are needed to estimate the model. See Hsiao (2003) for an overview of the traditional approaches to initial conditions in random effects models.

[26] We are aware that this is a restrictive assumption. We impose it for the sake of tractability. With autocorrelation, we would need to resort to simulation techniques, which may not converge to a global maximum given the complicated functional form of the conditional likelihood owing to the large number of equations in our model.

[27] $Z_{iT} = (z_{iT}, \cdots, z_{i1})'$.

integrate out the individual effect. Thus, the joint distribution of $((y_{iT}, ws_{iT}), \cdots, (y_{i1}, ws_{i1}))$ conditional only on observables is given by:

$$\begin{aligned} l_i(\beta,\delta,\theta) &= p((y_{iT}, ws_{iT}), \cdots, (y_{i1}, ws_{i1}) \mid Z_{iT}, ws_{i0}, y_{i0}; \beta,\delta,\theta) \\ &= \int_{\mathbb{R}} \prod_{t=1}^{T} f(y_{it} \mid X_{it}, c;\beta) g(ws_{it} \mid z_{it}, ws_{it-1}, Y_{it-1}, c;\delta) h(c \mid Z_{iT}, ws_{i0}, y_{i0};\theta) dc. \end{aligned} \tag{5}$$

Therefore, the log-likelihood for the whole sample can be written as:

$$\mathcal{L}(\beta,\delta,\theta) = \sum_{i=1}^{n} \ln [l_i(\beta,\delta,\theta)]. \tag{6}$$

4.2. A logit approach

We need to provide specific functional forms for the conditional densities of poverty status, work status and the individual effect. Since work status is a multinomial variable taking on $J>2$ different values,[28] obtaining ML estimates for β and δ is computationally very expensive. Therefore, for tractability purposes, we use a logit approach to model the distribution of poverty status and the multinomial distribution of work status. Accordingly, the conditional density of poverty status is defined as:

$$f(y_{it} \mid X_{it}, c;\beta) = \frac{[\exp(\beta X_{it} + c)]^{y_{it}}}{1 + \exp(\beta X_{it} + c)} \tag{7}$$

Likewise, the distribution of work status is given by the multinomial logit density:[29]

$$\begin{aligned} & g(ws_{it} \mid z_{it}, ws_{it-1}, Y_{it-1}, c;\delta) \\ &= \frac{\prod_{j=1}^{J} \left[\exp\left(\delta_z^j z_{it} + \delta_{ws}^j ws_{it-1} + \delta_y^j y_{it-1} + \delta_c^j c\right)\right]^{1\{ws_{it}=j\}}}{\sum_{m=1}^{J} \exp\left(\delta_z^m z_{it} + \delta_{ws}^m ws_{it-1} + \delta_y^m y_{it-1} + \delta_c^m c\right)}, \end{aligned} \tag{8}$$

where we normalize $\delta^1 = 0$ so that $\delta^j, j=2,\ldots,J$ are identified. Note that *past* work status affects the likelihood of being poor in two ways: (i) via a *direct* effect captured by β_{ws-1}, and (ii) via an *indirect* effect captured by $\delta^j{}_{ws}$ that operates through the likelihood of currently holding a specific work status (i.e. the *feedback* effect).

To complete the specification, we assume that the individual effect is normally distributed with variance σ and with mean:

$$h(c \mid Z_{iT}, ws_{i0}, y_{i0};\theta) = \frac{1}{\sigma}\phi\left(\frac{c - \gamma_z \bar{Z}_i - \gamma_{ws} ws_{i0} - \gamma_y y_{i0}}{\sigma}\right), \tag{9}$$

where $\phi()$ denotes the standard normal density.[30]

Because poverty is determined at the household level, the vector z_{it} includes information on family size and on the number of additional workers in the household so as to account for variations in household composition crucial in determining the household's poverty status. Additionally, all regressions include controls for the respondent's age, health status, marital status, educational attainment and regional unemployment rates. We also include up to three lags of poverty status ($k=3$). We choose "permanent employment" as the baseline work status ($ws_{it}=1$), i.e. $\beta_{ws_1}=0$. Finally, we approximate the integral in Eq. (5) using the Gauss–Hermite quadrature.

4.3. Average partial effects

To facilitate the interpretation of our estimates, we calculate the average partial effects (APE). (Wooldridge, 2002b) proposes alternative methods to compute APEs in the presence of unobserved heterogeneity. We follow the most general method, which requires no additional identification assumptions in the calculation of the *direct* APEs and *total* APEs. Direct APEs measure the impact of a regressor on poverty *ceteris paribus*. For instance, the direct APE of being unemployed relative to being employed on a permanent basis during the previous period is computed as the difference between the expected poverty status (conditional on the respondent's present work status) when unemployed and the expected poverty status when employed on a permanent basis during the previous period. Total APEs estimate the average impact of a lagged variable (e.g. past temporary work) on the individual's likelihood of being poor. It includes both *direct* and *indirect* or feedback effects. Using the previous example, it is computed as the difference between the expected poverty status when unemployed and the expected poverty status when employed on a permanent basis during the previous period, independently of the respondent's current work status.

According to Wooldridge (2002b), a consistent estimator of the direct APE for a binary regressor x_r in our model is given by:

$$\begin{aligned} \widehat{APE}_d(x_r) &= \frac{1}{n}\sum_{i=1}^{n}\int_{\mathbb{R}} \Big[E\Big(y_{it} \mid X_{-r} = \bar{X}_{-r}, x_r = 1, c;\hat{\beta}\Big) \\ &\quad - E\Big(y_{it} \mid X_{-r} = \bar{X}_{-r}, x_r = 0, c;\hat{\beta}\Big)\Big] h\Big(c \mid Z_{iT}, ws_{i0}, y_{i0};\hat{\theta}\Big) dc \\ &= \frac{1}{n\hat{\sigma}}\sum_{i=1}^{n}\int_{\mathbb{R}} \left[\frac{\exp\left(\hat{\beta}_{-r}\bar{X}_{-r} + \hat{\beta}_r + c\right)}{1 + \exp\left(\hat{\beta}_{-r}\bar{X}_{-r} + \hat{\beta}_r + c\right)} \right. \\ &\quad \left. - \frac{\exp\left(\hat{\beta}_{-r}\bar{X}_{-r} + c\right)}{1 + \exp\left(\hat{\beta}_{-r}\bar{X}_{-r} + c\right)}\right] \phi\left(\frac{c - \hat{\gamma}_z \bar{Z}_i - \hat{\gamma}_{ws} ws_{i0} - \hat{\gamma}_y y_{i0}}{\hat{\sigma}}\right) dc, \end{aligned} \tag{10}$$

where $\bar{X}_{-r}$ represents the regressors in X_{it}, with the exception of x_r.[31]

Total APE effects can be consistently estimated by:

$$\begin{aligned} & \widehat{APE}_T(x_r) = \\ &= \frac{1}{n}\sum_{i=1}^{n}\int_{\mathbb{R}}\Bigg[\sum_{j=1}^{J}\Bigg[E\Big(y_{it} \mid \bar{X}_{-r,ws}, ws_t = j, x_r = 1, c;\hat{\beta}\Big) P\Big(ws_t = j \mid \bar{X}^*_{-r,ws} x_r = 1, c;\hat{\delta}\Big) \\ &\quad - E\Big(y_{it} \mid \bar{X}_{-r,ws}, ws_t = j, x_r = 0, c;\hat{\beta}\Big) P\Big(ws_t = j \mid \bar{X}^*_{-r,ws}, x_r = 0, c;\hat{\delta}\Big)\Bigg]\Bigg] \cdot \\ &\quad \cdot h\Big(c \mid Z_{iT}, ws_{i0}, y_{i0};\hat{\theta}\Big) dc \\ &= \frac{1}{n\hat{\sigma}}\sum_{i=1}^{n}\int_{\mathbb{R}}\Bigg[\sum_{j=1}^{J}\Bigg[\frac{exp\left(\hat{\beta}_{-r,ws}\bar{X}_{-r,ws} + \hat{\beta}_{ws_j} + \hat{\beta}_r + c\right)}{1 + exp\left(\hat{\beta}_{-r,ws}\bar{X}_{-r,ws} + \hat{\beta}_{ws_j} + \hat{\beta}_r + c\right)} \\ &\quad \times \frac{exp\left(\hat{\delta}^j_{-r}\bar{X}^*_{-r} + \hat{\delta}^j_r + \hat{\delta}^j_c c\right)}{\sum_{m=1}^{J} exp\left(\hat{\delta}^m_{-r}\bar{X}^*_{-r} + \hat{\delta}^m_r + \hat{\delta}^m_c c\right)} - \frac{exp\left(\hat{\beta}_{-r,ws}\bar{X}_{-r,ws} + \hat{\beta}_{ws_j} + c\right)}{1 + exp\left(\hat{\beta}_{-r,ws}\bar{X}_{-r,ws} + \hat{\beta}_{ws_j} + c\right)} \\ &\quad \times \frac{exp\left(\hat{\delta}^j_{-r}\bar{X}^*_{-r} + \hat{\delta}^j_c c\right)}{\sum_{m=1}^{J} exp\left(\hat{\delta}^m_{-r}\bar{X}^*_{-r} + \hat{\delta}^m_c c\right)}\Bigg]\Bigg] \phi\left(\frac{c - \hat{\gamma}_z \bar{Z}_i - \hat{\gamma}_{ws} ws_{i0} - \hat{\gamma}_y y_{i0}}{\hat{\sigma}}\right) dc, \end{aligned} \tag{11}$$

where $\bar{X}_{-r,ws}$ includes all the regressors in $\bar{X}_{-r}$, except for $w\bar{s}_t$, and $\bar{X}^*_{-r}$ represents the subset of elements of $\bar{X}_{-r}$ in equation (8). In addition, $\hat{\beta}_{ws_j}$ is the coefficient estimate of the present work status dummy associated to the jth work status category.

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[28] Specifically, $J=9$ or 6, depending on whether we distinguish by contract type or not.

[29] A limitation of the multinomial logit is the Independence of Irrelevant Alternatives assumption, which imposes strong restrictions on the covariance matrix of the error terms. However, allowing for a more flexible structure would render the estimation intractable.

[30] Additional interaction terms between $\bar{Z}_i$, ws_{i0} and y_{i0} were included in the estimated regressions.

[31] For multinomial variables represented by a set of dummy variables, such as work status, the direct APE for category j is obtained by replacing in the above expression "$x_r=1$" with "$x_{r_1}=0, x_{r_2}=0, \cdots, x_{r_j}=1, \cdots$" and "$x_r=0$" with "$x_{r_1}=0, x_{r_2}=0, \cdots, x_{r_j}=0, \cdots$", where x_{r_j} is the dummy variable associated with category j.

Table 4
Poverty equation (males).

Variable	By work status		By contract type	
	Age≤35 coeff. (S.E.)	Age>35 coeff. (S.E.)	Age≤35 coeff. (S.E.)	Age>35 coeff. (S.E.)
Work status				
Temporary worker	0.1015 (0.1544)	0.3233** (0.1540)		
Six month contract			0.5866*** (0.2211)	0.7414*** (0.2323)
7–12 month contract			0.0533 (0.2003)	0.4377** (0.2225)
13+ month contract			−0.2513 (0.2680)	0.1608 (0.2523)
Other temporary contract			−0.0802 (0.2052)	0.4602** (0.1927)
Other worker	0.8115*** (0.1983)	1.0266*** (0.2192)	0.8119*** (0.1980)	1.1077*** (0.2176)
Self-employed/family business	0.9149*** (0.1865)	0.3160* (0.1845)	0.8968*** (0.1843)	0.5344*** (0.1873)
Unemployed	0.6643*** (0.1849)	0.9287*** (0.1714)	0.6664*** (0.1813)	0.7856*** (0.1700)
Out of the labor force	0.8607*** (0.2034)	0.1586 (0.1873)	0.8753*** (0.1997)	−0.0082 (0.1829)
Temporary worker last year	−0.0332 (0.1624)	−0.0563 (0.1534)		
Six month contract last year			0.0753 (0.2272)	0.1346 (0.2381)
7–12 month contract last year			0.1166 (0.1990)	0.1764 (0.2191)
13+ month contract last year			−0.1711 (0.2641)	−0.0672 (0.2511)
Other temporary contract last year			−0.4661** (0.2281)	0.1073 (0.1939)
Other contract last year	0.5223*** (0.1995)	0.0918 (0.2266)	0.4877** (0.1990)	0.1826 (0.2247)
Self-employed/family business last year	0.4347** (0.1959)	0.1660 (0.1791)	0.3814** (0.1937)	0.3149* (0.1822)
Lagged unemployed	0.2824* (0.1713)	0.2509 (0.1610)	0.2241 (0.1703)	0.3139** (0.1594)
Lagged out of the labor force	0.1685 (0.1862)	0.3468* (0.1778)	0.1142 (0.1841)	0.3315* (0.1752)
State dependence				
Poor last year	1.4427*** (0.0825)	1.4642*** (0.0733)	1.4355*** (0.0827)	1.4933*** (0.0724)
Poor two years ago	0.8675*** (0.0856)	1.0172*** (0.0760)	0.8716*** (0.0859)	1.0321*** (0.0756)
Poor three years ago	0.8007*** (0.0841)	0.6860*** (0.0765)	0.7933*** (0.0843)	0.6918*** (0.0763)
σ	0.1626** (0.0737)	0.3746*** (0.0650)	0.1659** (0.0758)	0.1263** (0.0521)
Log likelihood	−11295.1	−9484.9	−13788.5	−10792.8
Wald test p-value	<0.0001	<0.0001	<0.0001	<0.0001
No. of observations	9158	11,732	9158	11,732

*** denotes statistical significance at the 1% level, ** indicates 5% significance level, and * represents 10% significance level. All the regressions include a constant term, age, a health status dummy, marital status, family size, number of additional workers in the household, educational attainment dummies, the regional unemployment rate, and year dummies. The baseline group is permanent workers.

5. Results

In this section, we examine the link between poverty and present and past temporary employment. The APEs allow us to distinguish between a direct and an indirect or feedback effect of past temporary employment on poverty. As noted earlier, feedback effects are of particular interest in the case of past temporary employment since they can raise workers' poverty exposure via job instability or via their transition to work statuses with a high poverty risk.

We estimate our model separately for men and women to capture gender differences in the use of fixed-term contracts as well as in their link to poverty. Additionally, we carry out the estimation separately for individuals less than 35 years old and for individuals 35 years of age and older to address differences in the temporary jobs held by younger versus older workers.[32] This is of interest if younger workers accept temporary jobs with mediocre working conditions as a means to enter and advance in internal labor markets. Finally, we further differentiate according to the duration of the work contract held by the worker. Longer lasting temporary work contracts may signal a higher level of work commitment between the worker and the firm and, possibly, a higher likelihood of contract conversion to a permanent work status in the near future. If that is the case, we would expect workers with longer lasting work contracts to enjoy greater work attachment and a lower likelihood of life in poverty than their counterparts with short-lived fixed-term contracts.

The estimated coefficients and standard errors for men and women are displayed in Tables 4 and 5, respectively. Both of these tables also display the parameter sigma, which captures individual heterogeneity and reveals its significant role in explaining the likelihood of life in poverty. Tables 6 and 7 then show the corresponding APEs. Given the purpose of this study, we focus our discussion on the direct and total effects of present and past temporary work that are significantly impacting workers' poverty exposure.

5.1. Poverty and temporary work among men

We first look at the estimates for men in Tables 4 and 6. The figures in Table 4 indicate that only ongoing temporary employment is directly linked to a greater likelihood of life in poverty among men. If we do not distinguish by the type of temporary work contract held, temporary work only seems to be associated to a greater poverty risk among older men. The differential link between poverty and ongoing temporary employment among younger versus older men hints on the potentially dissimilar usage of fixed-term contracts by workers in these two age groups. In particular, younger male temporary workers may use fixed-term contracts as a stepping-stone. Additionally, as in other southern European countries, the differential impact of temporary employment on the poverty likelihood of young men as opposed to their older counterparts may be due to fact that young men are more likely to still live with their parents.[33] The first row in

[32] The age of 35 is a cutoff point often used in other papers, perhaps owing to the average age at which individuals finish college. Nonetheless, our findings were robust to other cutoff ages we experimented with, such as 30.

[33] See Ayllón (2009b). While we do not account for the type of living arrangement, we do control for whether the respondent is married. Since a large fraction of young men move out from their parental home when they get married, controlling for marital status (along with age, family size, and the number of working adults in the household) is likely to already take into account whether the individual resides with his parents. Furthermore, our results are robust to the estimation of separate regressions for young and older men according to their marital status. Results from these estimations are available from the authors upon request.

Table 5
Poverty equation (females).

Variable	By work status		By contract type	
	Age ≤ 35 coeff. (S.E.)	Age > 35 coeff. (S.E.)	Age ≤ 35 coeff. (S.E.)	Age > 35 coeff. (S.E.)
Work status				
Temporary worker	0.9030*** (0.2693)	0.4999* (0.2778)		
Six month contract			1.2090*** (0.3114)	0.8492** (0.3839)
7–12 month contract			0.7524** (0.3150)	−0.0778 (0.3973)
13+ month contract			0.6172 (0.3803)	0.6496 (0.4576)
Other temporary contract			0.5989 (0.4144)	0.7428* (0.3872)
Other worker	1.2469*** (0.2865)	0.5592** (0.2652)	1.2539*** (0.2879)	0.5755** (0.2651)
Self-employed/family business	1.4363*** (0.3140)	0.6858** (0.2855)	1.4414*** (0.3154)	0.7640*** (0.2857)
Unemployed	1.3974*** (0.2800)	0.4645* (0.2548)	1.4370*** (0.2798)	0.4288* (0.2538)
Out of the labor force	1.4393*** (0.2840)	0.1334 (0.2477)	1.4826*** (0.2824)	0.1542 (0.2488)
Temporary worker last year	0.0596 (0.2757)	0.2591 (0.2816)		
Six month contract last year			0.1281 (0.3270)	0.2969 (0.4020)
7–12 month contract last year			0.2254 (0.3080)	0.3643 (0.3647)
13+ month contract last year			−0.4921 (0.4441)	0.0553 (0.4919)
Other temporary contract last year			−0.7001 (0.5404)	0.4127 (0.4509)
Other contract last year	0.3243 (0.2877)	0.6783*** (0.2609)	0.2863 (0.2889)	0.7097*** (0.2596)
Self-employed/family business last year	0.6476** (0.3159)	0.7175** (0.2806)	0.6102* (0.3169)	0.7989*** (0.2794)
Lagged unemployed	0.3662 (0.2662)	0.6631*** (0.2477)	0.3320 (0.2666)	0.6649*** (0.2480)
Lagged out of the labor force	0.3591 (0.2680)	0.4816* (0.2473)	0.3285 (0.2676)	0.5272** (0.2468)
State dependence				
Poor last year	1.4928*** (0.0778)	1.6323*** (0.0672)	1.4914*** (0.0781)	1.6376*** (0.0672)
Poor two years ago	0.8966*** (0.0820)	1.0605*** (0.0712)	0.8931*** (0.0822)	1.0640*** (0.0712)
Poor three years ago	0.8624*** (0.0798)	0.8000*** (0.0710)	0.8645*** (0.0800)	0.8000*** (0.0709)
σ	0.1356 (0.0908)	0.1153 (0.0754)	0.1854** (0.0868)	0.0483 (0.0749)
Log likelihood	−11131.4	−10511.9	−12706.7	−10992.0
Wald test *p*-value	<0.0001	<0.0001	<0.0001	<0.0001
No. of observations	9119	12517	9119	12517

*** denotes statistical significance at the 1% level, ** indicates 5% significance level, and * represents 10% significance level. All the regressions include a constant term, age, a health status dummy, marital status, family size, number of additional workers in the household, educational attainment dummies, the regional unemployment rate, and year dummies. The baseline group is permanent workers.

Table 6
Average partial effects (males).

	Age ≤ 35		Age > 35	
	Contemp	Lagged	Contemp	Lagged
$\hat{P}$ (*poor* = 1|X = $\bar{x}$, permanent worker)	5.37%		6.66%	
Work status				
Temporary worker	0.54%	−0.21% [0.49%]	2.37%	−0.38% [1.61%]
Six month contract	3.87%	0.52% [1.89%]	6.34%	0.94% [4.18%]
7–12 month contract	0.28%	0.82% [1.68%]	3.28%	1.25% [3.37%]
13+ month contract	−1.14%	−1.07% [−0.50%]	1.07%	−0.43% [0.97%]
Other temporary contract	−0.39%	−2.57% [−1.31%]	3.48%	0.74% [3.15%]
Other worker	5.94%	4.02% [5.72%]	11.04%	1.30% [4.79%]
Self-employed/family business	6.81%	3.01% [8.18%]	4.18%	2.37% [5.20%]
Unemployed	4.56%	1.65% [3.80%]	6.84%	2.36% [6.23%]
Out of the labor force	6.58%	0.80% [3.64%]	−0.05%	2.51% [3.66%]
State dependence				
Poor last year		15.92% [16.38%]		16.97% [19.00%]
Poor two years ago		8.16%		10.32%
Poor three years ago		7.22%		6.28%

Direct and *Total* (direct plus feedback) average partial effects reported. *Total* average partial effects in squared brackets.

Table 6 shows that the predicted poverty rate of older men with permanent jobs is 6.66%. The likelihood of life in poverty among older men with fixed-term contracts is 2.37 percentage points higher than for their counterparts with open-ended contracts. As such, the predicted poverty rate of older male temporary workers is 9.03%. As we further distinguish according to the duration of the fixed-term contract held by the worker, we find that the contemporaneous poverty risk endured by older temporary workers is largely driven by the higher poverty risk associated to short-lived temporary contracts. Indeed, the contemporaneous predicted poverty rate endured by older male temporary workers with short-term contracts is approximately 13% (6.66% plus 6.34 percentage points),[34] whereas their poverty rate if they held a one-year fixed-term contract is 9.94% (6.66% plus 3.28 percentage points).

What is the link between poverty and past temporary work? In answering this question, it would be erroneous to solely look at the direct impact of past temporary work on poverty in Tables 4 and 5 and conclude that past temporary work is unrelated to the likelihood of

[34] As a reference, it is worth noting that, relative to their counterparts with open-ended contracts, younger men with short-term contracts have a contemporaneous predicted poverty rate of 9.24% (5.37% plus 3.87 percentage points).

Table 7
Average partial effects (females).

	Age≤35		Age>35	
	Contemp	Lagged	Contemp	Lagged
$\hat{P}$ *(poor* = 1|X = $\bar{x}$, permanent worker)	3.12%		7.79%	
Work status				
Temporary worker	4.34%	0.40% [1.79%]	4.51%	1.76% [3.28%]
Six month contract	6.60%	0.90% [3.54%]	8.70%	1.98% [2.89%]
7–12 month contract	3.27%	1.64% [3.54%]	−0.54%	2.51% [3.66%]
13+ month contract	2.51%	−2.65% [−0.71%]	6.13%	0.33% [1.29%]
Other temporary contract	2.41%	−3.46% [−1.37%]	7.29%	2.90% [5.32%]
Other worker	7.00%	2.14% [5.62%]	5.27%	5.68% [8.01%]
Self-employed/family business	8.83%	5.25% [10.83%]	7.56%	6.65% [9.85%]
Unemployed	8.78%	2.54% [6.46%]	3.69%	5.22% [6.67%]
Out of the labor force	9.27%	2.51% [7.40%]	1.18%	3.90% [4.07%]
State dependence				
Poor last year		17.67% [19.52%]		21.50% [22.49%]
Poor two years ago		9.05%		12.15%
Poor three years ago		8.66%		8.52%

Direct and *Total* (direct plus feedback) average partial effects reported. *Total* average partial effects in squared brackets.

life in poverty. In so doing, we would be ignoring the highly significant feedback or indirect effect of past temporary work on poverty via its link to respondents' present work status (see Table A in the appendix). Therefore, for those instances in which fixed-term employment is linked to a higher poverty risk contemporaneously, we also evaluate the total (direct plus indirect effects) effect of past temporary employment, which is displayed in brackets in Tables 6 and 7. For instance, past temporary work is linked to a higher poverty risk among older men (of approximately 1.61 percentage points) relative to past permanent employment. The poverty rate of older men with temporary jobs in the past goes up to 8.27% relative to 6.66% for older men without past temporary assignments. When we distinguish according to the duration of the fixed-term contract held by the worker in the past, we find that six-month contracts (linked to higher poverty rates contemporaneously) are also associated to a 4.18 percentage point higher poverty risk and, thus, to a 10.84% poverty rate. Therefore, past temporary work in short-lived contracts can have long lasting poverty implications, as the poverty rate only drops from 13% to 11% after one year. Finally, relative to past permanent employment, one-year fixed-term contracts are associated to an also high 10.03% poverty rate among older male workers.

5.2. Poverty and temporary work among women

Tables 5 and 7 display our results for women. Unlike previously seen for men, temporary employment is linked to a 4.34 to 4.51 percentage point higher likelihood of life in poverty among all women relative to permanent employment. As a result, the predicted poverty rate for female temporary workers ranges between 7.46% among younger women and 12.30% among their older counterparts. Thus, the magnitude of the contemporaneous link between poverty and temporary work is about half of what we observe for the unemployed. Furthermore, this poverty exposure only drops to 4.91% (3.12% plus 1.79 percentage points) for younger women and to 11.07% (7.79% plus 3.28 percentage points) for their older counterparts within a one-year period. Therefore, the link between poverty and temporary work appears to be long lasting.

As we distinguish according to the length of the work contract held by the employee, we find that, as with men, it is short-term employment that is more strongly associated to a higher poverty risk among women. Specifically, fixed-term contracts lasting up to six months are associated to a contemporaneous poverty rate of 9.72% (3.12% plus 6.60 percentage points) among younger women and of 16.49% (7.79% plus 8.70 percentage points) among their older counterparts. Six-month contracts can also have a long lasting link to poverty, only lowering the poverty rate to 6.66% (3.12% plus 3.54 percentage points) among younger women and to 10.68% (7.79% plus 2.89 percentage points) among older women over a one-year period. One-year contracts are also associated to a higher contemporaneous exposure to life in poverty among women, but that link only seems to prevail among younger women.

5.3. Discussion of gender differences

Overall, there are various gender similarities and differences in terms of the link between poverty and temporary work worth noting. Among the similarities, we first find that short-lived temporary employment of up to 6-months' duration is significantly linked to a greater poverty risk among all men and women. Second, past temporary employment never has a significant direct link to poverty among men or women. Yet, past temporary employment has significant feedback effects on male and female poverty exposure as can be seen in Table A in the appendix.[35] As a result, we find that the link between short-term employment and poverty can be relatively long lasting.

Perhaps the most notable gender difference is the fact that temporary work is only linked to a higher contemporaneous poverty exposure among older men, whereas it is associated to a greater contemporaneous poverty risk among all women. The differential impact of temporary work by age can be understood on the basis of a distinctive usage of temporary contracts as a stepping-stone among younger workers. Likewise, gender differences could be explained by a differential use of fixed-term contracts by men and women. For instance, it may be the case that younger men most commonly use temporary employment as a stepping-stone in their careers, whereas a higher percentage of younger women use temporary employment to earn a secondary household income. Additionally, gender differences could be explained, to some extent, by gender discrimination in the labor market, women's lesser involvement in unions and work councils, and/or by women's interrupted career and labor force participation patterns.[36]

[35] A similar table distinguishing by type of work contract is available from the authors.

[36] In this regard, it is worth noting that when we estimate our model for young and older women according to their marital status, the negative impact of temporary employment (and of other work statuses) is much larger among older married women than among older unmarried women. This finding may be partially due to the differences in labor force attachment between the two groups.

At any rate, the results in Tables 4 through 7 reveal long-lived poverty state dependence for both men and women. Yet, among older workers, poverty state dependence is often more acute among women than men, possibly signaling the greater employment and income growth opportunities available to men. How strong is poverty state dependence? As (Cantó, 2002), who reports that up to 39% of her sample is still in the same income decile a year later, we find a significant degree of poverty state dependence after one year. Specifically, men who were poor one year earlier endure poverty rates anywhere between 16 and 17 percentage points higher than their non-poor counterparts. These percentages range between 18 and 22 in the case of women. As a result, men and women who were poor one year earlier endure poverty rates ranging between 21 and 24% and between 21 and 30%, respectively. Nevertheless, for both men and women, poverty state dependence rates decrease significantly after two years. For instance, male poverty rates for men who were poor two and three years ago range between 13 and 17% and between 12 and 13%, correspondingly. Among women, those percentages range between 12 and 20% in the case of women who were poor two years ago and between 12 and 17% for their counterparts who where poor three years ago. Finally, it is worth noting that these high poverty state dependence rates are also in line with those found by Ayllón (2009a) using ECHP data for a variety of European countries. She reports a significant positive poverty state dependence in most European countries. However, poverty state dependence proves to be more persistent in countries like Spain, Italy or Ireland as opposed to Denmark, Finland or the U.K., which she argues is one of the reasons for the youth to leave the parental home much later in Southern European countries.

6. Conclusions

This paper examines the link between poverty and past and present temporary employment while accounting for state dependence and unobserved heterogeneity possibly correlated with the regressors.

Our results first reveal that women, particularly older women, as well as older men holding temporary jobs are more likely to live in poverty than their permanent counterparts. Much of the contemporaneous negative impact of temporary employment is due to short-lived temporary work contracts, which appear more harmful than longer temporary contracts. Specifically, temporary work contracts lasting up to six months are linked to a 4 to 9 percentage point higher poverty exposure among all men and women relative to permanent work contracts. As a result, the predicted contemporaneous poverty rate of temporary workers reaches 13% among older males, 10% among younger women, and up to 16% among older women. The link between temporary employment and poverty is further emphasized among older men and younger women holding one-year contracts, who endure a 3 percentage point higher contemporaneous likelihood of life in poverty than their permanent counterparts. As such, the predicted contemporaneous poverty rates among temporary workers with one-year contracts reach 10% among older men and 6% among younger women.

What may explain the observed differences by age and gender? The differential welfare impact of temporary employment among younger versus older male workers may be explained by the divergent usage of temporary employment by each group. In particular, younger men may use temporary work contracts as a stepping-stone, whereas their older counterparts may resort to temporary employment as a means to earn an additional income. Gender differences in the poverty implications of temporary work for younger women relative to younger men could be due to a variety of factors. These may range from gender discrimination in the labor market, to women's lesser involvement in unions and work councils, and/or to women's more interrupted career and labor force participation patterns. Alternatively, it is possible that a higher percentage of younger women use temporary employment to earn a secondary household income versus as a stepping-stone in their careers as it may be the case among younger men.

Second, we find that temporary employment has a long lasting link to poverty via its feedback effects. The latter perpetuate poverty exposure via job instability and the transition to work statuses with higher poverty risks.

Finally, we document a significant degree of state dependence for both men and women. In particular, poverty state dependence seems to last well beyond a one year period. For instance, being poor three years ago is linked to a 6 to 9 percentage point higher likelihood of life in poverty, reaching poverty rates of approximately 13% among all men, 12% among younger women, and 16% among older women.

In sum, while unable to provide unequivocal evidence of a causal relationship between temporary work and poverty, our results endorse the existence of a solid link between temporary work and poverty among women and older men relative to permanent employment. Furthermore, the poverty risk appears to be long lasting via significant *indirect* or feedback effects. This link seems to be primarily driven by the harmful effect of short-lived fixed-term contracts, thus signaling the importance of work attachment. As such, from a policy-wise perspective, our findings underscore the value of longer lived work contracts and policies aimed at facilitating the transition from fixed-term to open-ended contracts in fighting poverty.

Acknowledgements

We are grateful to Benita Aybar López at INE for her help with survey related questions. Cynthia Bansak and participants at the SAE, the IRRA annual meetings, and a seminar at the IRP at Madison, Wisconsin, provided useful comments.

Appendix A

Table A
Work status equations (multinomial logit coefficient estimates).

Variable	Present work status				
	Temp coeff. (S.E.)	Other coeff. (S.E.)	Self. coeff. (S.E.)	Unemp. coeff. (S.E.)	Out LF coeff. (S.E.)
Males aged ≤ 35					
Past work status					
Temporary worker	2.5526***	2.5153***	1.2931***	2.1280***	1.7796***
	(0.0990)	(0.2460)	(0.2042)	(0.2328)	(0.3323)
Other worker	2.4318***	3.4990***	2.2449***	2.8210***	3.0644***
	(0.1688)	(0.2884)	(0.2771)	(0.2910)	(0.3736)
Self-employed	1.9746***	3.0456***	5.4730***	2.5483***	2.8525***
	(0.1973)	(0.3307)	(0.2254)	(0.3165)	(0.4140)
Unemployed	3.0499***	3.7093***	3.0435***	4.1305***	3.8222***
	(0.1460)	(0.2712)	(0.2242)	(0.2542)	(0.3378)
Out of labor force	2.7365***	3.6920***	3.0580***	3.7481***	5.2402***
	(0.1743)	(0.2914)	(0.2595)	(0.2755)	(0.3497)
Poor last year	0.6333***	0.6844***	0.8710***	0.4327**	0.1989
	(0.1337)	(0.1769)	(0.1726)	(0.1772)	(0.1968)
c_i	−0.1472	−0.5171***	−0.8015***	−1.8391***	−2.2114***
	(0.0912)	(0.1306)	(0.1510)	(0.1739)	(0.1963)
Males aged > 35					
Past work status					
Temporary worker	3.6602***	2.7210***	1.0700***	3.7848***	2.1104***
	(0.1560)	(0.2495)	(0.2605)	(0.2293)	(0.2850)
Other worker	3.0082***	4.1017***	2.5288***	4.0253***	3.0752***
	(0.2457)	(0.3025)	(0.3314)	(0.3221)	(0.3928)

(continued on next page)

Table A (*continued*)

Variable	Present work status				
	Temp coeff. (S.E.)	Other coeff. (S.E.)	Self. coeff. (S.E.)	Unemp. coeff. (S.E.)	Out LF coeff. (S.E.)
Males aged>35					
Past work status					
Self-employed	2.0707***	3.3525***	5.7251***	4.1717***	4.6338***
	(0.2491)	(0.3113)	(0.2338)	(0.3255)	(0.3076)
Unemployed	4.2799***	3.6389***	3.5125***	6.1950***	4.8483***
	(0.1981)	(0.2979)	(0.2657)	(0.2378)	(0.2532)
Out of labor force	4.2286***	4.4538***	5.0015***	6.0909***	7.6400***
	(0.3680)	(0.4666)	(0.3974)	(0.3673)	(0.3483)
Poor last year	0.7026***	0.8141***	0.4720***	0.4558***	0.3769**
	(0.1443)	(0.1983)	(0.1781)	(0.1673)	(0.1901)
c_i	−0.8437***	−0.6535***	−1.7038***	0.4074*	0.9783***
	(0.1325)	(0.1754)	(0.1681)	(0.2206)	(0.2133)
Females aged≤35					
Past work status					
Temporary worker	2.7582***	1.6862***	1.1490***	1.7644***	1.7059***
	(0.1364)	(0.2458)	(0.3780)	(0.2876)	(0.3246)
Other worker	2.7235***	4.1567***	2.7192***	3.2752***	3.1835***
	(0.2070)	(0.2692)	(0.4123)	(0.3349)	(0.3710)
Self-employed	2.2681***	2.5214***	6.6014***	2.9550***	3.6727***
	(0.3351)	(0.4513)	(0.3733)	(0.4364)	(0.4545)
Unemployed	3.2871***	3.6911***	3.5567***	4.2451***	3.9188***
	(0.1804)	(0.2591)	(0.3407)	(0.3081)	(0.3401)
Out of labor force	3.6245***	4.2958***	4.6314***	4.7241***	6.4813***
	(0.2457)	(0.3105)	(0.3785)	(0.3496)	(0.3814)
Poor last year	0.5674***	0.2515	0.5339**	0.2251	−0.0004
	(0.1999)	(0.2267)	(0.2606)	(0.2378)	(0.2424)
c_i	−0.3322**	−0.8332***	−0.6818***	−2.2983***	−2.5377***
	(0.1325)	(0.1963)	(0.2409)	(0.2333)	(0.2603)
Females aged>35					
Past work status					
Temporary worker	4.5182***	2.3900***	1.4280***	3.4659***	2.5040***
	(0.2137)	(0.2836)	(0.5466)	(0.3061)	(0.2948)
Other worker	3.2623***	4.6603***	2.7584***	4.0300***	3.7009***
	(0.2903)	(0.2758)	(0.4981)	(0.3404)	(0.3032)
Self-employed	2.9209***	3.1929***	5.7153***	4.5999***	4.5115***
	(0.5016)	(0.5103)	(0.4996)	(0.5060)	(0.4920)
Unemployed	4.9018***	4.6354***	4.9146***	6.3750***	5.8497***
	(0.2728)	(0.2774)	(0.4263)	(0.3136)	(0.2715)
Out of labor force	4.6974***	5.0444***	4.6451***	6.9792***	7.9153***
	(0.3679)	(0.3804)	(0.4715)	(0.3709)	(0.4028)
Poor last year	1.2988***	0.7203***	1.0248***	0.7223***	0.5373**
	(0.2580)	(0.2529)	(0.2883)	(0.2532)	(0.2407)
c_i	−0.0760	−0.3055	−2.3988***	1.0703***	−0.7674**
	(0.3141)	(0.3529)	(0.3754)	(0.3909)	(0.3789)

*** denotes statistical significance at the 1% level, ** indicates 5% significance level, and * represents 10% significance level. All the equations regressions include a constant term, age, a health status dummy, marital status, family size, number of additional workers in the household, educational attainment dummies, the regional unemployment rate, and year dummies. The baseline group is permanent workers.

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