# Do temporary contracts cause wage discrimination?

## A quantile treatment effect analysis for Europe

Giulia Santangelo*

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**Abstract**

The purpose of this paper is to asses whether the wide diffusion of temporary contracts in several European countries can cause wage penalties. Using the 2007 wave of the European Union Statistics on Income and Living Conditions (EUSILC) cross sectional data referred to six European countries (Austria, Spain, Ireland, Italy, Portugal, United Kingdom), I apply the estimation procedure for the quantile treatment effect parameters proposed by Firpo (2007) and then compare obtained results with standard quantile regression. Considering the six countries as a whole, there exists a wage discrimination for temporary workers which decreases along the wage distribution ranging from 13,4% at the 10th percentile to 7% at the 90th percentile. I also point out that the price effect explains the most part of the wage differential and concerns specially low-earning workers. Further, I note that to evaluate the incidence of the price effect it is necessary to distinguish between Mediterranean countries, which experienced the largest drop in the Employment Protection Legislation (EPL), and Central and North European countries, where there has been a lower or null trend increase in the incidence of temporary employment.

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# 1. Introduction

Since the beginning of the nineties a wide increase of temporary employment has been observed in almost all European countries. This increasing trend can be related to the necessity to improve economic performance in European countries by means of higher labor market flexibility, in accordance to the economic literature (Bentolila and Bertola, 1990)

The coexistence of workers with temporary employment contracts with workers with stable (i.e. long-term) employment relationships has increased the dualism or segmentation in labor markets of several EU Member States. Boeri (2010b) argues that this dualism is related to the two-tier reform strategy which has been enacted in Europe since the 1980s. The two-tier structure focused on promoting flexibility 'at the margin' – through the deregulation of temporary contracts and/or the introduction or development of agency work and other contracts of limited duration – while keeping existing rules on permanent contracts largely unchanged.

The positive correlation between two-tier EPL reforms and the share of employees in temporary work is shown by the trend increase in temporary employment, as a share of total number of employees, which has been registered since the mid-1980s. According to the Organization for Economic Cooperation and Development (OECD) (OECD, 2010), the incidence of temporary contracts for short-tenured employees presents higher rates, greater than 45%, in countries that have implemented two-tier EPL reforms through the liberalization of temporary contracts, i.e. Germany, Greece, Spain, France, Italy, Portugal and Sweden, with peaks of 80% in Spain and 70% in Portugal, while temporary contracts account for a relatively low share of new recruitment in Romania (about 10%), in the Baltic countries, in the UK (about 17%), Ireland (about 19%) and Denmark (about 25%).

On the one hand, it is true that temporary employment has been useful in increasing the employment rate in most of the EU countries. Boeri (2010b) indicates that labor market reforms increasing flexibility at the margin have been recently paying out in terms of employment growth, because they have a transitional honeymoon, job creating effect. On the other hand, several studies look at the macroeconomic consequences of the two-tier reforms. Blanchard and Landier (2002) argue that the macroeconomic effects of marginal flexibility may be perverse, since they involve high turnover in fixed term jobs, leading in turn to higher, rather than lower, unemployment.

Furthermore, in recent years there is an increasing debate on the negative effect of temporary contracts. In particular, the debate focuses on precariousness, i.e. the fact that temporary contracts are usually characterized by lower wages, lower welfare protection, higher unemployment spells, low incidence of switching to a permanent contract.

In this paper I address the issue of wage differential between temporary and permanent. According to Rosen (1974), workers with the same level of competence should receive different wages if their working conditions are different. His theory of 'Compensating differentials' involves therefore a positive wage differential for temporary workers like a risk premium in return for wider flexibility accorded to employers or like a premium for the high probability of being dismissed. However evidence constantly controverted this theory both at individual level and at firm level. Empirical research performed on different countries prefigure the existence of a negative wage differential for atypical workers, even after controlling for their various observed individual characteristics. Comi and Grasseni (2009) perform the analysis of the wage gap between temporary and permanent jobs in nine European countries and assess that having a fixed-term contract penalizes low–skilled workers more than high–skilled ones, and decompose the wage differential across the entire wage distribution, finding that workers with the same characteristics as temporary workers would receive higher wages if they worked on permanent contracts in almost all the countries considered.

The aim of this paper is to investigate further the wage differential between temporary and permanent along the wage distribution. I make use of the methodology proposed by Firpo (2007) to compute a quantile treatment effect, i.e. identifying a causal effect of having a temporary contract. This procedure allows to compare the wage distribution of temporary workers with the counterfactual wage distribution of permanent workers, that would arise if their characteristics were distributed like those of temporary workers, and to asses whether at each quantile there exists a wage differential between temporaries and permanents induced by the kind of contract.

The econometric analysis is performed using the 2007 wave of the "European Union Statistics on Income and Living Conditions" (EUSILC) cross sectional data of Austria, Spain, Ireland, Italy, Portugal and the United Kingdom. For these countries it is available the current gross wage, while for other countries it is only available the labor income of the previous year. As covariates I make use of the following individual variable: gender, age, education, experience, skill, full-time or part-time contract, sector, being an immigrant, task variables (abstract, routine, service, offshore).

Results obtained with the quantile treatment effect method by Firpo are compared with standard quantile regression estimates (Koenker and Basset, 1978). Estimating quantile treatment effect parameters and regression coefficients allows us to analyze the effect of temporary contracts on the whole wage distribution, both for low-earning and for high-earning workers. Moreover, the methodology allows to detect how much of the wage penalty derived by quantile regression is due to self-selection of workers or to a real price effect (discrimination).

I apply the Firpo (2007) methodology first to the Europe as a whole and then to each single country, as data referred to various Member States permit to evaluate and compare wage effects for countries which experienced very different temporary employment incidence and evolution, and to investigate if country heterogeneity is at work.

Considering the six countries as a whole, I show that there exists a wage discrimination for temporary workers which decreases along the wage distribution ranging from 13,4% at the 10th percentile to 7% at the 90th percentile and that this price effect explains the most part of the wage differential and concerns specially low-earning workers.

Analyzing singularly each country, I find that for the Spanish case the price effect almost totally absorbs the wage gap between temporaries and permanents at the extremes of the wage distribution, both at the lower and at the upper tail, while for the Italian case a strong price effect which can almost completely explain the wage gap appears only in the upper tail of the wage distribution. Austria exhibits wage penalties and price effects which are strongly higher than other countries in the lower tail of the wage distribution while for UK as for Ireland it is not possible to asses the existence of an heterogeneous price effect along the wage distribution. I note therefore that it is necessary to distinguish between Mediterranean countries, which experienced the largest drop in the Employment Protection Legislation (EPL), and Central and North European countries, where there has been a lower or null trend increase in the incidence of temporary employment.

The rest of the paper is organized as follows. The next section presents the theoretical and empirical framework. Section 3 describes the dataset used for the empirical investigation and reports sample descriptive statistics. Section 4 presents the estimation methodology. Section 5 presents the empirical results and Section 6 concludes.

# 2. Theoretical and empirical framework

The evaluation of causes and effects of the widespread use of temporary employment has been the focus of large literature. Several authors provided some theoretical explanations for the utilization of temporary contracts by firms:

- Temporary jobs can be used as a screening device (OFlaherty and Siow, 1995). Since ability cannot be perfectly observed, the employers can follow a mechanism that is often called "up or out rules". They can assume workers with temporary contracts in order to screen them, and permanently retain the ones who proved to be more productive.

- Temporary contracts can be stipulated to maximize workers' on the job effort. In fact, it can be argued that fixed-term contracts can have a positive effect on effort if workers perceive that the rehiring probability depends on past performance (Dolado, García-Serrano and Jimeno, 2002)

- Temporary employment is used by firms as a flexible mechanism to adjust employment to fluctuations in the business cycle (Blanchard and Landier, 2002). Temporary workers can in fact represent a buffer to face demand shocks and to adapt the workforce to the level of the demand, as profit

> maximizing behavior requires. Instead, if only permanent contracts are available, firms are forced to inefficiently retain a share of the workforce when demand is low, making lower profits. (Berton, Devicienti and Pacelli, 2007)

On the other hand, in the matter of the negative effects of labor market flexibility, Haltiwanger, Lehmann and Terrell (2003) observe that it may imply, at least for workers, job insecurity, unemployment and wage inequality, underlying the same features because of those Sylos Labini (2004) argued that there exists an optimum level of flexibility, which does not coincide at all with the maximum one.

Concentrating on the effects of temporary jobs on workers, Cappellari and Leonardi (2006) provide an estimate of the earnings instability associated with a fixed-term contract. Using Italian panel data they find that workers on fixed-term contracts can experience between 10% and 100% more instability than the workers on permanent contracts, depending upon the portion of the career spent on fixed-term contracts.

Other empirical researches study the mean wage penalty associated with temporary contracts in one country.

For the US, after adjusting for characteristics such as age and educational attainment, Segal and Sullivan (1995) find that the wage differential associated with temporary employment varies widely by occupation, from 34 percent less for blue-collar workers to 10 percent less for pink-collar workers to 2 percent more for white-collar workers.

Booth, Francesconi and Frank (2002) study the UK case using data from the British Household Panel Survey – which disaggregates temporary work into seasonal or casual jobs and fixed-term contract jobs – and find that the creation of temporary jobs as a substitute for permanent jobs – in the desire to increase labor market flexibility – comes at a cost, as on average temporary workers report lower levels of job satisfaction (at least in some components), receive less work related training than their counterparts in permanent employment and receive lower wages.

The Irish labor market has been studied by Layte, O'Connell and Russell (2008), who, using data from a nationally representative survey of employees and three different measures of quality, find that those employed on fixed term and casual contracts do tend to be employed in jobs which have poorer conditions. Controlling for personal and firm characteristics, OLS estimates point out that non-permanent employees receive a significantly lower mean hourly wage.

With regards to Spain, Dolado, García-Serrano and Jimeno (2002) observe that there have been some unexpected negative consequences stemming from the existence of a segmented/dual labor market such as lower investment in human capital, higher wage pressure, a more unequal distribution of unemployment duration, lower labor mobility and fertility rates and larger wage dispersion. Specifically Jimeno and Toharia (1993) argue that there might be substantial wage effects involved in the widespread use of temporary contracts, as fixed-term workers earn approximately 9-11% than permanents.

Several studies focus on the Italian labor market. Naticchioni, Devicienti and Ricci (2011) analyze the effects of an increase of the portion of temporary contracts on firm's performances, merging Longitudinal Survey on Firms and Labor (RIL) and AIDA datasets. They show that increasing the percentage of temporary employment, in addition to decreasing labor costs, can also have a negative impact on firm's productivity. Lucidi and Raitano (2009) notice on average a loss in the monthly wage for temporary workers equal to 21.2%. By the Oaxaca decomposition they find that the 8.5% of this medium differential can be ascribed to the different composition of the temporary and permanent workforce, while the 13.7% of it represents a discriminating wage penalty which affects temporary workers. Picchio (2006) estimates the impact of a temporary contract on wage by fixed effects and reveals a significant wage penalty for temporary workers of about 12%, after controlling both for individual-specific components and observables firm-specific effects.

Barbieri and Cutuli (2009) and Bosio (2009) move a step forward from previous studies by evaluating the gap across the wage distribution. The formers, using It-Silc and Shiw datasets, prove that wage losses for temporary workers since the 1990s are quite stable and significant regardless of the statistical method used to estimate them, from the simplest OLS on cross sectional data to BE and FE regress. Bosio applies the quantile regression model and the Machado-Mata decomposition to SHIW dataset and shows that the unconditional wage gap between temporary and permanent is wider at the bottom of the distribution (around 30%) and then tends to decrease monotonically in the top of distribution, and thus this wide effect at the bottom of the distribution can be interpreted as a sort of discrimination in low-wage jobs for fixed-term workers.

Brown and Session (2005) study the wage gap associated with a temporary job in nine European and some OECD countries using data from the British Social Attitudes Survey and International Social Survey Programme. Estimating a Mincerian wage equation for all employees, they find evidence of wage discrimination against fixed-term contract employees, as workers employed under such contracts receive significantly lower earnings than their permanent contract counterparts, even after controlling for personal and job characteristics.

Comi and Grasseni (2009) extend the analysis of the wage gap between temporary and permanent jobs in nine European countries evaluating the gap across the entire wage distribution by the quantile regression approach. With EU-SILC data they show that in some countries the fixed-term wage gap decreases as higher quantiles are considered, and that having a fixed-term contract penalizes low–skilled workers more than high–skilled ones. They finally decompose the wage differential across the entire wage distribution using the procedure developed by Machado and Mata and find that workers with the same characteristics as temporary workers would receive higher wages if they worked on permanent contracts in almost all the countries considered.

# 3. Data

The EU-SILC database provides comparable, cross-sectional and longitudinal multidimensional data on income, poverty, social exclusion and living conditions in the European Union. EU-SILC stands for "European Union Statistics on Income and Living Conditions" and adheres to European Union regulations number 1177/2003 (European Community, 2003), which has been elaborated following the increasing request for information from national and European institutions. This database is anchored in the European Statistical System (ESS) and is collated by Eurostat. The EU-SILC survey is established to provide data on structural indicators of social cohesion and constitutes one of the main data source for European Union periodical reports about social condition and poverty diffusion in member states.

EU-SILC was launched in 2004 in 13 member states plus Norway and Iceland and has reached its full scale extension with the 25 MS + NO, IS in 2005. Later it has been completed by Turkey, Romania, Bulgaria and Switzerland. My analysis concentrates on six countries: Austria (AT), Spain (ES), Ireland (IE), Italy (IT), Portugal (PT) and the United Kingdom (UK), because for these countries it is available the current gross wage. For other countries it is only available the labor income of the previous year and these have been therefore excluded from the analysis, because all individual variables used in the estimation procedure are referred to the current month and it is hence necessary to consider also for the income index the current one.

The database includes two kinds of data: longitudinal data, pertaining to individual-level changes over time, and cross-sectional data, pertaining to a certain time period with variables on income, poverty, social exclusion and other living conditions. I use cross sectional data referred to year 2007.

The reference population of EU-SILC is all private households and their current members residing in the territory of the MS at the time of data collection. Persons living in collective households and in institutions are generally excluded from the target population.

In each country I analyze sample units have been selected by a stratified two-stage sampling, except for Austria, for which a simple random sampling has been used.

According to the Commission Regulation on sampling and tracing rules (N°1982/2003 of 21 October 2003, §7.4), weighting factors shall be calculated as required to take into account the units' probability of selection, non-response and, as appropriate, to adjust the sample to external data relating to the distribution of households and persons in the target population, such as by sex, age (five-year age groups), household size and composition and region (NUTS II level), or relating to income data from other national sources where the Member States concerned consider such external data to be sufficiently reliable. I use personal cross-sectional weights for all household members, of all ages (target variable RB050) in order to draw inference on individual basic demographic variables for the population of all individuals living in private households.

EU-SILC database contains some information collected at household level, such as social exclusion and housing-condition, and other 'basic' (income, education, basic labor information and second job) and 'detailed' variables (health, access to health care, detailed labor information, activity history and calendar of activities) collected and analyzed at the person-level. To study the effects of temporary contracts on wages I use this latter individual variables. In particular I analyze the effects of temporary contracts on current hourly wages adjusted for Purchasing Power Parity (lch_wage_ppp), controlling for sector, task, full-time or part-time contract, skill, experience, education, age, gender and immigration.

We defined temporary workers following the EU-SILC classification as those not working under a permanent contract. Thus classified among temporary workers are those workers with defined durations of their contracts, but also persons with seasonal jobs, persons engaged by an employment agency or business and hired out to a third party to perform a 'work mission' (unless they have a work contract of unlimited duration with the employment agency or business), and persons with specific training contracts. If there is no objective criterion for the termination of job or work contracts, these should be regarded as permanent or of unlimited duration.

I excluded from the analysis individuals aged under 16 and individuals aged 65 and over, thus we ended up with a sample of 44153 observations distributed by country as follows, Austria (AT) 5888, Spain (ES) 10154, Ireland (IE) 3843, Italy (IT) 13838, Portugal (PT) 3380 and the United Kingdom (UK) 7050.

Sample descriptive statistics referred to the six analyzed countries and to Europe as a whole are reported in the tables below. In Table 1 countries are ordered according to the percentage of temporary workers. Spain, Portugal and Italy are the countries with the highest levels of concentration of temporary workers, which are higher than the medium level calculated on the whole European sample. The UK has the lowest percentage of temporary contracts, 3,84%. From values shown in Table 2 and in Table 3 we can see how individual variables are distributed in Europe as a whole. The largest class of age, level of education and skill are the medium ones. The sector with the highest number of clerks is the manufacturing.

Table 1: Percentages of temporary and permanent workers in European countries

| Country | Percentage of temporary workers | Percentage of permanent workers |
|---|---|---|
| Europe | 13.36 | 86.64 |
| Spain | 25.08 | 74.92 |
| Portugal | 20.80 | 79.20 |
| Italy | 14.40 | 85.60 |
| Austria | 10.44 | 89.56 |
| Ireland | 9.08 | 90.92 |
| United Kingdom | 3.84 | 96.16 |

Table2: Percentages of personal characteristics in Europe

| Personal characteristics | | Percentages |
|---|---|---|
| Gender | Female | 46.33 |
| | Male | 53.67 |
| Immigrant | Yes | 6.72 |
| | No | 93.28 |
| Age | [16,30) | 21.10 |
| | [30,45) | 44.62 |
| | [45,64] | 34.28 |
| Education level | 1 | 28.06 |
| | 2 | 45.55 |
| | 3 | 26.39 |
| Skill | Top | 35.27 |
| | Medium | 37.17 |
| | None | 27.56 |

Tables 3: Percentages of work characteristics in Europe

| Personal characteristics | | Percentages |
|---|---|---|
| Contract | Part time | 15.18 |
| | Full time | 84.82 |
| Experience level | 1 | 10.15 |
| | 2 | 11.86 |
| | 3 | 12.06 |
| | 4 | 14.51 |
| | 5 | 13.41 |
| | 6 | 12.25 |
| | 7 | 10.02 |
| | 8 | 15.74 |
| Sector | Wholesale | 13.40 |
| | Manufacturing | 29.75 |
| | Transport | 10.19 |
| | Financial intermediation and business activities | 12.19 |
| | Public administration | 09.07 |
| | Education and Health | 18.78 |
| | Other services | 06.62 |

# 4. Methodology

If we are interested in detecting the partial effect of a variable in the special case of a binary explanatory variables, we can estimate the treatment effect.

Defining various treatment effect needs to specify the counterfactual framework, which was pioneered by Rubin (1974) and allows us to detect for each variable an outcome with or without treatment. Define $T$ as the indicator variable of treatment, where $T = 1$ denotes treatment and $T = 0$ otherwise. For an individual $i$, if $T_i = 1$, we observe $Y_i\left(1\right)$; otherwise, if $T_i = 0$, we observe $Y_i\left(0\right)$. Here $Y_i\left(1\right)$ and $Y_i\left(0\right)$ are, respectively, the potential outcomes of receiving and not receiving the treatment. Whereas a given individual $i$ is either treated or not, we define the observed outcome as $Y_i = Y_i\left(1\right) \cdot T_i + Y_i\left(0\right) \cdot \left(1 - T_i\right)$. Assume that we also observe a random vector $X_i$ of covariates with support $\chi \subset \mathbb{R}'$. The triple $\left(Y\left(1\right), Y\left(0\right), T\right)$ represents a random vector from the underlying population of interest inside which it is not possible to observe both $Y\left(1\right)$ and $Y\left(0\right)$, because an individual cannot be in both states.

To measure the effect of treatment we face a problem of missing data as we are interested in the difference in the outcomes with and without treatment, $Y\left(1\right) - Y\left(0\right)$. The treatment effect is a random variable and is individual specific. Rosenbaum and Rubin (1983) estimated the average treatment effect, that is the expected effect of treatment on a randomly drawn person from the population, which averages across the entire population, $ATE = E(Y(1) - Y(0))$.

If we want to exclude from the examined population who would never be eligible for treatment and calculate the mean effect only for those who actually received the treatment, we can estimate the average treatment effect on the treated, $ATT = E(Y(1) - Y(0) \mid T = 1)$.

If the treatment effect is heterogeneous and varies along the outcome distribution, it can be more accurately estimated through the quantile treatment effect (QTE). In the original definition from Doksum (1974) and Lehmann (1974) the QTE corresponds, for any fixed percentile, to the horizontal distance between two cumulative distribution functions. In defining QTE as the treatment effect at the individual level, both Doksum and Lehmann implicitly assumed the hypothesis of *rank preservation*, according to that an observed individual maintains his rank in the distribution regardless of his treatment status. As quantile treatment effects are simple differences between quantiles of the marginal distributions of potential outcomes, if rank preservation holds, then the simple differences in quantiles turn out to be the quantiles of the treatment effect.

Various quantile treatment effect parameters differ by the subpopulation to which they refer. As an analog of the average effect, the overall quantile treatment effect (QTE) is the quantile treatment effect parameter for the whole population under consideration while the quantile treatment effect on the treated (QTT) is the parameter for those individuals subject to treatment.

Let $\tau$ be a real in $(0,1)$. As in Firpo (2007), the QTE and QTT parameters can then be expressed as follows:

- QTE: $\Delta_\tau \equiv q_{1,\tau} - q_{0,\tau}$,
  where $q_{j,\tau \equiv \inf_q} Pr[Y(j) \leq q] \geq \tau$, $j = 0, 1$.
- QTT: $\Delta_{\tau|T=1} \equiv q_{1,\tau|T=1} - q_{0,\tau|T=1}$
  where $q_{j,\tau|T=1 \equiv \inf_q} Pr[Y(j) \leq q \mid T = 1] \geq \tau$, $j = 0, 1$.

Estimation of average and quantile treatment effect parameters is based on the *exogeneity* assumption, which was termed by Rubin the *unconfoundedness* assumption and characterizes the selection on observables branch of the program evaluation literature. It states that selection to treatment is based on observables variables so, given a set of observed covariates, individuals are randomly assigned either to the treatment group or to the control group. Thanks to the *selection on observables* assumption it is possible, as demonstrated by Firpo, to calculate the marginal quantiles for the treated and for the control outcomes without computing the corresponding conditional quantiles.

The estimation procedure for the quantile treatment effect parameters proposed by Firpo[1] (2007) consists in a semiparametric two-step method. In the non parametric first step the propensity score is estimated and in the second

[1] The methodology proposed by Firpo to calculate the estimators for unconditional quantile treatment effects and unconditional quantile treatment effects on the treated is here implemented in the Stata software using and integrating the sintax suggested by Frölich and Melly (2010).

step the final estimators are computed through the difference between the solutions of two separate minimization problems. The identification of QTE and QTT parameters is based on the following strong ignorability and uniqueness of quantiles assumptions.

1. Strong Ignorability (Rosenbaum and Rubin (1983))

Let $(Y(1), Y(0), T, X)$ have a joint distribution. Then, for all $x$ in $\chi$, the support of $X$, the following conditions hold:

- *Unconfoundedness*: Given $X$, $(Y(1), Y(0))$ is jointly independent from $T$.
- *Common support*: For some $c > 0$, $c < p(x) < 1 - c$.

The *unconfoundedness* assumption is a fundamental assumption of estimation methods of treatment effects and is in fact at the base also of the identification of average effects. It states that assignment to treatment depends only on the observable individual characteristics and not on the unobservables determining $Y(1)$ and $Y(0)$, and it certainly holds if $T$ is a deterministic function of observed covariates $X$. Selection is not made on the strength of the potential outcomes. Therefore, if we can observe enough information (contained in $X$) that determines treatment, then $(Y(1), Y(0))$ might be independent of $T$, conditional of $X$. Loosely, even though $(Y(1), Y(0))$ and $T$ might be correlated, they are uncorrelated once we partial out $X$. The *common support* assumption states that for almost all values of X both treatment assignment levels have a positive probability of occurrence. Secondly, the Firpo (2007) methodology assumes that the distribution functions of the potential outcomes are continuous and not flat at the $\tau$-percentile for some values of $\tau \epsilon (0,1)$. This implies that the respective quantiles are well defined and unique.

2. Uniqueness of Quantiles:

For $j = 0, 1$, $Y(j)$ is a continuous random variable with support in $\mathbb{R}$ and where the following statements apply:

- There are nonempty sets $\mathcal{Y}_1$ and $\mathcal{Y}_0$, such that $\mathcal{Y}_j = \{\tau \epsilon (0,1); Pr[Y(j) \leq q_{j,\tau} - c] < Pr[Y(j) \leq q_{j,\tau} + c]\}$, $\forall c \epsilon \mathbb{R}, c > 0$.
- There are nonempty sets $\mathcal{Y}_{1|T=1}$ and $\mathcal{Y}_{0|T=1}$, such that $\mathcal{Y}_{j|T=1} =$ $\left\{\tau \epsilon (0,1); Pr\left[Y(j) \leq q_{j,\tau|T=1} - c \mid T = 1\right] < Pr\left[Y(j) \leq q_{j,\tau|T=1} + c \mid T = 1\right]\right\}$, $\forall c \epsilon \mathbb{R}, c > 0$.

Assumptions 1 and 2 allow to write $q_{1,\tau}$, $q_{0,\tau}$, $q_{1,\tau|T=1}$ and $q_{0,\tau|T=1}$ as implicit functions of observed data, and to estimate both QTE and QTT from the data on $(Y, T, X)$. It is not necessary to impose any restrictions on the joint distribution of $(Y, T, X)$, as the estimation technique used here is semiparametric. It extends to quantile treatment effects the characteristics of average treatment effects.

The estimation method proposed by Firpo is a reweighed version of the procedure used by Koenker and Basset (1978) for the quantile estimation problem. Koenker and Basset estimate quantiles as solution of the minimization of the sum of asymmetrically weighted absolute residuals, where different weights are assigned to positive and negative residuals. The $\tau$th quantile, for example, is so calculated,

$$\hat{q}_{\tau} \equiv arg \min_{q} \sum_{i=1}^{N} \rho_{\tau} \left( Y_i - q \right),$$

where the check function $\rho_{\tau}(\cdot)$ evaluated at a real number $a$ is $\rho_{\tau}(a) = a \cdot (\tau - \mathbb{I}\{a \leq 0\})$. Sample quantiles can in practice be found by minimizing a sum of check functions.

In the method proposed by Firpo, in order to calculate the quantile treatment effect it is necessary first to estimate quantiles of two different distributions of the control group and of the group who receives the treatment. To estimates the quantiles of the two groups, the check functions $\rho_{\tau}(\cdot)$ defined by Koenker and Basset are premultiplied respectively by the weights $\hat{w}_{1,i}$ and $\hat{w}_{0,i}$, in order to reflect the fact that the distribution of the covariates differs in this two groups. The estimator for the $\tau$th quantile turns, for $j = 0, 1$, into

$$\hat{q}_{\tau} \equiv arg \min_{q} \sum_{i=1}^{N} \hat{w}_{j,i} \cdot \rho_{\tau} \left( Y_i - q \right).$$

The weight used to estimate the sample quantile of the $Y(1)$ distribution, $\hat{q}_{1,\tau}$, is

$$\hat{w}_{1,i} = \frac{T_i}{N \cdot \hat{p}(X_i)}.$$

It is used to weigh each unit of the treated group, while the weight used to estimate the sample quantile of the $Y(0)$ distribution, $\hat{q}_{0,\tau}$, is

$$\hat{w}_{0,i} = \frac{1 - T_i}{N \cdot (1 - \hat{p}(X_i))},$$

which is utilized for each unit of the control group.

To identify the quantile treatment effect only for those individuals who actually received the treatment, quantiles $\hat{q}_{1,\tau|T=1}$ and $\hat{q}_{0,\tau|T=1}$ of the conditional distributions $(Y(1) \mid T = 1)$ and $(Y(0) \mid T = 1)$ have to be estimated. In this case units who belong respectively to the treatment and to the control group have to be weighted with weights

$$\hat{w}_{1,i|T=1} = \frac{T_i}{\sum_{l=1}^{N} T_l}$$

$$\hat{w}_{0,i|T=1} = \frac{\hat{p}(X_i)}{1 - \hat{p}(X_i)} \cdot \frac{1 - T_i}{\sum_{l=1}^{N} T_l}.$$

The so defined weights allow to correct for the selection on observables problem. In particular, weights $\hat{w}_{0,i|T=1}$ reweigh units who belong to the control group in order to calculate the conditional outcome $(Y(0) \mid T=1)$ that they would have risen if they they had received the treatment.

Estimators $\hat{q}_{1,\tau}$, $\hat{q}_{0,\tau}$, $\hat{q}_{1,\tau|T=1}$ and $\hat{q}_{0,\tau|T=1}$ are therefore traditional propensity-score weighting estimators, also known as inverse probability weighting. They are two-step estimators, because we first estimate the propensity score nonparametrically and then, in the second step, we minimize

$$G_{\tau,N}(q;\hat{p}) = \sum_{i=1}^{N} \hat{w}_{j,i} \cdot (Y_i - q) \cdot (\tau - \mathbb{I}\{Y_i \le q\}),$$

in order to obtain quantile estimators as solutions of this minimization problem.

Once defined the two sums of weighted check functions, the proposed estimators for quantile treatment effects can be obtained as the difference between the solutions of two minimizations:

$$Q\hat{T}E \equiv \hat{\Delta}_\tau \equiv \hat{q}_{1,\tau} - \hat{q}_{0,\tau}$$

$$Q\hat{T}T \equiv \hat{\Delta}_{\tau|T=1} \equiv \hat{q}_{1,\tau|T=1} - \hat{q}_{0,\tau|T=1}.$$

Firpo shows that the respective estimators $\hat{\Delta}_\tau$ and $\hat{\Delta}_{\tau|T=1}$ of QTE and QTT calculated by this procedure have large sample properties. $\hat{\Delta}_\tau$ and $\hat{\Delta}_{\tau|T=1}$ are (i) root-N consistent and (ii) asymptotically normal. He also presents a consistent estimation procedure for $V_\tau$ and $V_{\tau|T=1}$, the normalized asymptotic variance of$\hat{\Delta}_\tau$ and $\hat{\Delta}_{\tau|T=1}$. Finally, calculating the semiparametric efficiency bounds for QTE and QTT parameters under unconfoundedness of the treatment and unknown propensity score, Firpo proves that $\hat{\Delta}_\tau$ and $\hat{\Delta}_{\tau|T=1}$ are efficient in the class of semiparametric estimators.

# 5. Results

Wages related to different kinds of contract are firstly analyzed through the quantile regression methodology. I use a linear specification of wage equation, with the logarithm of the current hourly wage adjusted for Purchasing Power Parity as dependent variable, in order to compare earned income of workers who work a different number of hours and live in different countries. To evaluate the effect of temporary contracts on wages I put in the wage equation also control variables concerning individual characteristics such as age, gender, being an immigrant, education, and working feature as experience, skill, task, sector, full-time or part-time contract. The following equation represents hence the estimated wage equation:

$$\ln w_i = \delta_\theta \cdot temp_i + \beta_\theta \cdot X_i + \varepsilon_{\theta,i},$$

where $i$ indicates the observed individual and $\theta$ the considered quantile. $\ln w_i$ is the logarithm of the current hourly wage adjusted for Purchasing Power Parity,

$temp_i$ is the dummy variable which indicates if individual $i$ has a temporary contract, $X_i$ is the vector of explicative variables and $\varepsilon_{\theta,i}$ is the error term. Coefficients $\delta_\theta$ and $\beta_\theta$ are estimated for every considered quantile. Specifically I estimate the above-mentioned equation by nine quantiles of the distribution of log-wages, namely for $\theta = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9$. In this way, thanks to the quantile regression, it is possible to estimate different slope coefficients at different quantiles of the distribution of the dependent variable and to evaluate if the response of the dependent variable, hourly wage, to changes in the regressors varies along the wage distribution. In particular I can asses if the effect of a temporary contract with respect to a permanent one, represented by the coefficient $\delta_\theta$, is homogeneous or not along the wage distribution. In Table 4 it is possible to observe estimates of the coefficient related to temporary contracts for different regression quantiles.

The negative sign of all coefficients related to different quantiles indicates that a wage penalty is associated to temporary contracts, in the sense that workers who have a temporary contract receive lower wages with respect to workers with a permanent one. The coefficient of the dummy variable that takes value 1 if workers have temporary jobs, $\delta_\theta$, assumes as absolute value a maximum value equal to .2132397 and a minimum value equal to .1457363 and monotonically decreases along different quantiles of the wage distribution. This means that the negative effect on wages caused by a temporary job decreases along the wage distribution and is therefore stronger at the bottom of the distribution, where probably workers trapped in the secondary segment of the dual labor market are located.

Through the above used quantile regression I am not able to verify if the wage penalty suffered by temporary jobs compared with permanent ones is caused also by individual and job characteristics. For example, temporary workers are more likely to be younger and concentrated in certain occupations and sectors, and this can negatively affects their earned incomes. Thence, in order to isolate the effect of a particular type of contract and to evaluate how a temporary contract influences the wage compensations of a certain individual it is necessary to adopt another more accurate methodology, such as the quantile treatment effect, which allows us to take into account the existing individual and job heterogeneity in the characteristics.

In fact, with the quantile regression approach it is possible to asses whether a relation between the type of contract and the wage exists and whether this relation varies significatively across the quantiles of the wage distribution, but I am also interested in establishing if a causal effect exists, namely if the type of the contract is in itself the real cause of a wage penalty. To do this I need to evaluate the effect of temporary contracts all other conditions being equal. I need therefore to compare workers with all equal individual and working characteristics which differ only because of the type of the working contract, or alternatively we need to compare the wage outcomes of a same individual in the two distinct cases of a temporary contract and of a permanent contract. QTE approach allows us to obviate for the lack of such data, that only a randomized experiment could provide us.

Through the QTE approach in fact it is possible to construct the counterfactual distribution of outcomes of individuals belonging to the control group that would arise if they had received the treatment. Considering the temporary contract as a treatment variable, I construct the counterfactual distribution of permanent workers' wages that would arise if their characteristics were distributed like those of temporary workers. In this way I can compare temporary workers' wages with wages they would receive if they had a permanent contract, all other their individual and working conditions being equal, ensuring that, on the basis of the unconfoundedness assumption, no other variables have an impact upon the wage.

The unconfoundedness assumption asserts in fact, that, as selection is based only on observable characteristics $X$, if individuals have the same characteristics then treatment is randomized between them, and therefore, conditioning of $X$, is independent from their outcomes. The comparison between the wage of permanents and the wage of temporaries therefore allows us to identify the wage differential that is caused by a contract of temporary type.

In defining the counterfactual distributions of workers' wages I use as control variables the same covariates utilized in the quantile regressions. That is we compared similar permanent and temporary workers with respect to skill, experience, education, age, sex and immigration, sector, task, full-time or part-time contract.

The procedure proposed by Firpo allows to ensure similarity between the two groups and to correct for the selection on observables problem through the use of specific weights. Before comparing wage distributions, the group of permanents and the group of temporary workers are weighted with two different weighs computed on the basis on the propensity score[2], just to provide the distributions of covariates in the two groups to be very similar.

With quantile treatment effects estimates we are therefore able to identify what in the decomposition method introduced by Oaxaca (1973) and Blinder (1973) (OB) is defined as the "price or wage structure effect", that is how much of the wage difference is due to changes in the $\beta$'s given constant the set of the $X$. An other plausible cause of the wage differential is the so called "composition effect", that is much of the wage difference is due to changes in the composition of the labor force, the $X$, given the coefficients $\beta$. Comparing the quantile regression correlation coefficients between type of contract and wages, and QTE parameters I can asses how much of the wage differential is induced by a price effect and if also a composition effect exists.

From QTE estimates reported in Table 4 I note that the variation in the im-

[2]The propensity score, which is the probability for each individual of receiving the treatment treated, and in this case of having a temporary contract, is computed using the following individual variable: gender, age, education, experience, skill, full-time or part-time contract, sector, being an immigrant, task variables (abstract, routine, service, offshore) and their interactions (part_time*gender part_time*skill part_time*age part_time*experience part_time*education part_time*sector gender*immigrant gender*skill gender*education gender*sector immigrant*skill immigrant*age immigrant*experience immigrant*education immigrant*sector skill*age skill*experience skill*education skill*sector age*experience age*education experience*education).

pact across the quantiles of the distributions is not statistically significant, next to the 80th and 90th percentiles, that is for high-earning workers. The causal effect of a temporary contract on wages always assumes a negative sign, meaning that a temporal job induces a wage penalty on individuals. This wage gap between temporary and permanent workers is quite steady across the first part of the distribution (12%), but decreases clearly to the 60h and 70th percentiles.

All this means that workers who are located in the lower tail of the distribution and are therefore low-earning individuals are the ones more affected by the wage penalty. Secondly, as quantile regression coefficients are greater than price effects estimated by the QTE method, we can conclude that the treatment effect does not completely explain the wage gap between temporary and permanent workers and that probably the latter is due also to the composition of the labor force.

Calculating the quantile effect only on the subpopulation of individuals who actually received the treatment[3] and had therefore a temporal job, I obtain estimates of the causal effect on wages of the particular type of contract that are statistically heterogeneous along all the quantiles of the wage distribution. Restricting the considered sample, I obtain higher treatment effect (the QTT assumes a maximum value equal to 14,8% to the 70th percentile).

Also in this case, the difference between the quantile regression coefficients and the QT coefficients suggests that a causality model is necessary to assess how much of the wage gap has to be attributed to the causal effect induced by the kind of contract. According to the QTT parameters, it plays a big role along the whole wage distribution.

Generally, QTE and QTT estimates point out that a strong treatment effect exists across the wage distribution and that temporary workers are discriminated compared to the permanent ones because, given constant the set of their individual and working features, the type of contract itself induces a wage penalty and a reduction of their earnings.

[3]For the QTT parameters standard errors are estimated by bootstrapping the results 100 times. The coefficients have generally the expected signs and are conform to previous studies. The bootstrap is known to estimate the distribution of $\hat{b}(h)$ consistently (Hahn, 1995). The observations are resampled with replacement.

Table 4: Quantile regression, Quantile treatment effect and Quantile treatment effect on the treated coefficients for Europe

| lch_wage_ppp | Quantile Regression | QTE | QTT |
|---|---|---|---|
| Quantile 1 | -.2132397 *** | -.1340771*** | -.1348203 *** |
| Quantile 2 | -.2245032 *** | -.1152238 *** | -.1403701 *** |
| Quantile 3 | -.2050988 *** | -.132705 *** | -.1325572 *** |
| Quantile 4 | -.1942052 *** | -.1201143 *** | -.11158907 *** |
| Quantile 5 | -.1868395 *** | -.1365728 *** | -.1343908 *** |
| Quantile 6 | -.1826011 *** | -.0975921 *** | -.1309008 *** |
| Quantile 7 | -.1612555 *** | -.0716615 *** | -.1479187 *** |
| Quantile 8 | -.1473194 *** | -.0432203 | -.1111598 *** |
| Quantile 9 | -.1457363 *** | -.0267806 | -.0707323 *** |

*** indicates that the coefficient is significant at the 0.05 level.

## 5.1 Spain

That of Spain is a peculiar case where the regression coefficient associated with the variable that indicates a contract of temporary type doesn't show any heterogeneity It is in fact quite constant along the all wage distribution at a value of 15%. This means that all temporary workers, both low-earning and high-earning, face the same wage penalty associated with the temporary contract.

The treatment effect of a temporary contract calculated over all the individuals is significantly heterogeneous across the earning distribution but, in the case of Spain, shows a tendency opposite to that of all other analyzed countries. The effect in fact monotonically increases along the distribution, going from a value of 13,4% next to the 10th percentile to a value of 20,8% next to the 90th percentile, with a light peak next to the 70th percentile.

Estimates of the treatment effect calculated only on individuals who actually received the treatment fall into a smaller range, going as absolute value from a minimum value equal to 10,7% and a maximum value equal to 14,7% next to the 80th percentile. In this case the curve of the treatment effect along the wage distribution follows nearly a U-shaped distribution, with a minimum value equal to 10,7% constant for 40th, 50th and 60th percentiles.

Last of all, at the extremes of the wage distribution the treatment effect almost totally absorbs the wage gap between temporaries and permanents. Peculiarity of Spain's results can be explained by the fact that it is the country with the highest percentage of temporary workers (25,9% against the 13,5% medium value), although, together with Ireland, it is the country where the class of upper level of education is the largest one. This wide supply of temporary workers can induce a strong reduction of temporary wages, causing for example a so evident treatment effect.

Table 5: Quantile regression, Quantile treatment effect and Quantile treatment effect on the treated coefficients for Spain

| lch_wage_ppp | Quantile Regression | QTE | QTT |
|---|---|---|---|
| Quantile 1 | -.1516619 *** | -.1347862 *** | -.1316743 *** |
| Quantile 2 | -.1567149 *** | -.1384025 *** | -.1168503 *** |
| Quantile 3 | -.1492123 *** | -.1510575 *** | -.1110705 *** |
| Quantile 4 | -.1514428 *** | -.1564777 *** | -.1078599 *** |
| Quantile 5 | -.1533825 *** | -.1804535 *** | -.1079047 *** |
| Quantile 6 | -.1559127 *** | -.1788032 *** | -.1073885 *** |
| Quantile 7 | -.1590995 *** | -.2177801 *** | -.1406934 *** |
| Quantile 8 | -.1487375 *** | -.1949344 *** | -.1469829 *** |
| Quantile 9 | -.1486772 *** | -.2085626 *** | -.1157064 *** |

*** indicates that the coefficient is significant at the 0.05 level.

## 5.2 Portugal

The Portuguese case represents the only one where quantile regression coefficients associated to the temporary contract variable increase along the wage distribution. The F-tests of equality between quantiles states that the coefficient relative to the first quantile is not statistically different from the other ones. From the second quantile on, the value of the dummy variable coefficient varies between the -8,6%, at the 20th percentile, and -12,2% at the 80th percentile, with a slight decrease at the last quantile. Hence in Portugal the wage gap shows a gentle increasing tendency moving from the low-earning temporary workers to the high-earning temporary ones.

The variation in the impact of a temporary contract across the wage distribution is significant only for some quantiles in the case of the estimates obtained on the whole population, and is not statistically and substantively significant in the case of the subsample of individuals who are actually treated.[4] Hence for Portuguese workers it is not possible to state that the causal effect of a temporary contract is heterogeneous along the wage distribution if not only for the 20th, 30th, 50th and 90th percentiles.

Together with Spain, Portugal is one of countries where temporary contracts have the largest diffusion (percentage of temporary contract is equal to 20,%). An other feature that marks Portugal compared to other countries is that the largest class of education is the lowest one. This could suggest that the particular composition of the labor force influences the wage distribution specially in the upper tail.

Table 6: Quantile regression, Quantile treatment effect and Quantile treatment effect on the treated coefficients for Portugal

| lch_wage_ppp | Quantile Regression | QTE | QTT |
|---|---|---|---|
| Quantile 1 | -.0374935 | -.0240976 | -.0413182 |
| Quantile 2 | -.0866675 *** | -.0694095 *** | -.0829104 |
| Quantile 3 | -.0906427 *** | -.0865372 *** | -.0645386 |
| Quantile 4 | -.0896122 *** | -.0761892 | -.1002567 |
| Quantile 5 | -.117088 *** | -.1335315 *** | -.1165377 |
| Quantile 6 | -.1127824 *** | -.0932031 | -.0657555 |
| Quantile 7 | -.1071806 *** | -.0487901 | -.0287081 |
| Quantile 8 | -.1225866 *** | -.1383263 | -.0203511 |
| Quantile 9 | -.0925425 *** | -.2057164 *** | -.002028 |

*** indicates that the coefficient is significant at the 0.05 level.

[4] QTE estimates referred to Portugal must be interpreted with caution because weights $\hat{w}_{1,i}$ and $\hat{w}_{0,i}$, used to weigh respectively the treated group and the control group in order to make them comparable, are not able to make the two groups equal with respect to all control variables.

## 5.3 Italy

Quantile regression coefficients estimated on Italian data are conform to most countries results, since they report a strong wage loss among low-earning temporary workers and a gradual reduction of the penalty moving to the upper tail of the wage distribution, for high earning temporary workers.

Heterogeneity in the temporary contract's impact across the earnings distribution's quantiles is unmistakably significant, both statistically and substantively, both for the entire population and for the subsample of individuals who actually have a temporal job. In both case having a temporary contract causes a wage penalty which assumes values equal to about 18% next to the 10th percentile and monotonically decreases along the wage distribution fixing a lower wage loss for individuals who are located in the upper tail of the distribution and receive higher wages. However, comparing only temporary workers with the counterfactuals, QTT estimates indicate that next to the 90th percentile the penalty effect caused by a temporary contract is not statistically significant, and hence workers who receive higher wages are not affected in their earnings by the type of their contract.

With the exception of central percentiles, the light reduction of QTT estimates compared to the regression coefficients seems to signal that the wage gap can totally be explained by the treatment effect. Instead, to the 40th, 50th and 60th percentiles we obtain regression coefficients that are lightly lower than QTT parameters, meaning that also other factors influence the wage gap.

Table 7: Quantile regression, Quantile treatment effect and Quantile treatment effect on the treated coefficients for Italy

| lch_wage_ppp | Quantile Regression | QTE | QTT |
|---|---|---|---|
| Quantile 1 | -.2019819 *** | -.1823217 *** | -.1839226*** |
| Quantile 2 | -.1686675 *** | -.189242 *** | -.1541507*** |
| Quantile 3 | -.1541507 *** | -.1541507 *** | -.1570039*** |
| Quantile 4 | -.124845 *** | -.1649966 *** | -.1358016*** |
| Quantile 5 | -.1147732 *** | -.1438704 *** | -.1431007*** |
| Quantile 6 | -.1128539 *** | -.1244278 *** | -.1419687*** |
| Quantile 7 | -.113644 *** | -.1177831 *** | -.1177831*** |
| Quantile 8 | -.093095 *** | -.1053605 *** | -.1053605*** |
| Quantile 9 | -.0874199 *** | -.1053605 *** | -.0336857 |

*** indicates that the coefficient is significant at the 0.05 level.

## 5.4 Austria

As shown in Table 8, coefficients which represents the effect of a temporary contract on wages for the Austrian case assume higher values than the other countries of the sample. They are all statistically significant. This means that the wage differential caused by a temporary job is strongly wider in this country. Temporary workers get a 58,5% lower wage in the 10th percentile of the wage distribution and a 21,1% lower wage in the 90th percentile. Further this wage differential monotonically decreases along the distribution, ratifying that workers who are located at the bottom of the distribution and are therefore low-earning temporary workers are the ones more affected by the wage penalty associated with transitional occupations.

With the QTE approach we obtain treatment effect estimates that result statistically heterogeneous only in the central part of the wage distribution and assume lower values than the quantile regression coefficients (maximum value equal to 22,7% to the 60th percentile).

Concentrating only on the sample of treated individuals, we obtain QTT parameters which, similarly to the quantile regression estimates, show that the quantile treatment effect on the treated caused by a temporary contract is stronger in this country compared to the other considered countries. The variation in the impact across the quantiles of the distributions is unmistakably significant, both statistically and substantively, exclusive of the 90th percentile. The treatment effect monotonically decreases along the distribution, but differently from the QTE and other countries' estimates it assumes very high values next to the 10th and 20th percentiles equal to 83,2% and 73,9%.

This evidence of a so strong wage penalty can be induced from the particular composition of the labor force in Austria, where it is possible to observe a higher incidence of part-time workers, generally less skilled, younger and more concentrated around a medium level of education than in the other countries. Percentages of part-time, medium skilled and unskilled workers, with a second education level, part of the first class of age, are in fact higher than the medium values of the all sample, while percentages of top skilled workers with a level of education equal to the first or the third one are lower than the respective mediums calculated on the whole sample. Disparity between regression coefficients and QTT coefficients could therefore suggest that in addition to the effect induced by the kind of contract also other effects related to the composition of the workforce affect the wage distribution.

Table 8: Quantile regression, Quantile treatment effect and Quantile treatment effect on the treated coefficients for Austria

| lch_wage_ppp | Quantile Regression | QTE | QTT |
|---|---|---|---|
| Quantile 1 | -.5856841 *** | -.2351197 | -.8329092 *** |
| Quantile 2 | -.5609924 *** | -.1288329 *** | -.7391741 *** |
| Quantile 3 | -.4286184 *** | -.1855061*** | -.6013395 *** |
| Quantile 4 | -.3612528 *** | -.1814804*** | -.4769241 *** |
| Quantile 5 | -.2924756 *** | -.1862955*** | -.2821828 *** |
| Quantile 6 | -.2661055 *** | -.2270572*** | -.2819355 *** |
| Quantile 7 | -.2226229 *** | -.2298579 | -.2586946 *** |
| Quantile 8 | -.2173253 *** | -.1800251 *** | -.2411797 *** |
| Quantile 9 | -.2114179 *** | -.1512308 | -.1097574 |

*** indicates that the coefficient is significant at the 0.05 level.

## 5.5 Ireland

In Ireland the F-tests of equality between quantiles confirm the heterogeneity of the coefficients estimates only for some quantiles. In particular, with the quantile regression approach, only for the 10th, 20th, 50th, 60th and 70th percentiles of the wage distribution, a temporary contracts induces a wage penalty significatively different from the others percentiles.

Instead with the QTE approach, only workers situated at the 60th and 90th percentiles are affected by a wage loss caused by a temporary job. In particular temporary workers with the highest earnings, located at the upper tail of the distribution, suffer a strong wage penalty equal to about 40%.

Also in this case, such results can be caused by the particular composition of the labor force in Ireland, which counts the largest number of workers in the high-skilled, most aged and most educated workers.

Table 9: Quantile regression, Quantile treatment effect and Quantile treatment effect on the treated coefficients for Ireland

| lch_wage_ppp | Quantile Regression | QTE | QTT |
|---|---|---|---|
| Quantile 1 | -.1799033 *** | -.0939479 | -.0082942247 |
| Quantile 2 | -.062958 *** | -.0856097 | .0396674871 |
| Quantile 3 | -.05099 | -.0625458 | 0 |
| Quantile 4 | -.0437404 | -.087013 | 0 |
| Quantile 5 | -.0389815 *** | -.1025093 | -1.43051e-06 |
| Quantile 6 | -.06768 *** | -.1897557 *** | -.0018541813 |
| Quantile 7 | -.0499739 *** | -.2034087 | -.1013054848 |
| Quantile 8 | -.0147959 | -.24807 | -.1392176151 |
| Quantile 9 | .0105618 | -.3990045 *** | -.059841156 |

*** indicates that the coefficient is significant at the 0.05 level.

## 5.6 United Kingdom

In the case of United Kingdom, quantile regression coefficients referred to the extreme quantiles are not statistically significant. We can asses that the variation of coefficients is statistically significant only across the central quantiles of the distributions, from the 20th to the 60th percentile. Inside this range of the wage distribution the wage penalty associated to a temporary contract firstly increases and then decreases with a peak equal to the 13,6% to the 40th percentile, meaning that workers with a wage close to the median one are the ones more affected by a wage loss associated to the temporary contract.

QTE[5] and QTT estimates referred to the United Kingdom are always statistically not significant, signaling that the impact of a temporary contract is not significant heterogeneous across the earnings distribution's quantiles.

The UK one is a peculiar case, because it presents very skilled and experienced workers and above all it is the country with the lowest percentage of temporary workers, equal to 3,9%. Among the sample's countries in fact, UK is the only one where the largest classes are that of workers with the highest level of experience and, together with Ireland, the class of high skilled workers. Moreover it is distinguished from the others by the fact that the sector with the biggest number of clerks is not the manufacturing one but rather health care and education. All this factors, together with the high presence of unionized workers at the bottom of the wage distribution, can contribute to reduce the wage disparities across different quantiles.

Table 10: Quantile regression, Quantile treatment effect and Quantile treatment effect on the treated coefficients for United Kingdom

| lch_wage_ppp | Quantile Regression | QTE | QTT |
|---|---|---|---|
| Quantile 1 | -.0543471 | -.0569077 | -.0300742 |
| Quantile 2 | -.077548 *** | -.0953133 | -.0597244 |
| Quantile 3 | -.077548 *** | .0723205 | -.0699858 |
| Quantile 4 | -.1363094 *** | .1087103 | -.0575718 |
| Quantile 5 | -.1229924 *** | .0531795 | .0143876 |
| Quantile 6 | -.1190833 *** | -.020741 | -.0671160 |
| Quantile 7 | -.0687108 | -.0361595 | -.0571861 |
| Quantile 8 | -.0650972 | -.0412495 | -.0619845 |
| Quantile 9 | -.0468267 | .1305122 | -.0392584 |

*** indicates that the coefficient is significant at the 0.05 level.

[5] QTE estimates referred to United Kingdom must be interpreted with caution because weights $\hat{w}_{1,i}$ and $\hat{w}_{0,i}$, used to weigh respectively the treated group and the control group in order to make them comparable, are not able to make the two groups equal with respect to all control variables.

To sum up, estimates calculated on the whole sample of European countries show that temporary workers are affected by a wage penalty, which decreases along the wage distribution ranging from 21,3 at the 10th percentile to 14,5 at the 90th percentile. Quantile treatment effect on the treated (QTT) parameters allow us to detect how much of this wage gap can be attributed to the causal effect of a temporary contract. Values ranging from 13,4% to 7%, and being very low next to the 80th and 90th percentiles, indicate that the treatment effect explains the most part of the wage differential and concerns specially workers which are located in the lower tail of the wage distribution and are therefore low-earning workers.

Secondly, I perform the analysis distinctly on the different countries of the sample in order to evaluate the effects of temporary contracts in the EU Member States which exhibit considerable diversities in temporary employment incidence and evolution. I first look at Mediterranean countries, which experienced the most rapid and intense shift from rigid employment protection systems to flexibilised labor markets and applied a labor market deregulation focused on age-targeted characteristics. Results obtained for the Spanish case, which is the earliest since the mid-1980s and most extreme case of temps boom, indicate that the treatment effect almost totally absorbs the wage gap between temporaries and permanents at the extremes of the wage distribution, both at the lower and at the upper tail. Italy, which in tuns appear as an extreme case because it has been the country with the largest drop in the Employment Protection Legislation (EPL) subindex for temporary employment since the early 1990s, shows as Spain a strong causal effect of temporary contracts which can almost completely explain the wage gap in the upper tail of the wage distribution.

Finally I focus on Central and North European countries which generally applied a "skill-centred" strategy of deregulating labor market based more on the skill divide in the workforce (Barbieri and Cutuli, 2009). Austria, for example, exhibits wage penalties and price effects which are strongly higher than other countries in the lower tail of the wage distribution. Further results seem to indicate that also the composition of the labor force influences the wage distribution and probably partially compensates the price effect. Ireland and United Kingdom, together with Denmark, represent Member States characterized by relatively less stringent regulation for permanent contracts, where there has been no trend increase in the incidence of temporary employment. In Ireland it is possible to pick out a wage penalty only for some percentiles of the wage distribution but it is not possible to ascribe it to a treatment effect. For UK as for Ireland, the wage penalty does not affect workers located in the upper tail of the wage distribution and in addition it is not possible to asses the existence of an heterogeneous treatment effect along it.

# 6. Conclusions

To asses if temporary workers suffer a wage penalty caused by the kind of contract itself, I analyze hourly wages of permanents and temporaries.

I perform the econometric analysis using the 2007 wave of the European Union Statistics on Income and Living Conditions (EUSILC) cross sectional data referred to six European countries (Austria, Spain, Ireland, Italy, Portugal, United Kingdom), which can be assumed as representative of different ways of deregulating labor market. I calculate quantile treatment effects, considering the temporary contract as a treatment variable, through estimation procedure proposed by Firpo (2007), in order to asses whether and to what extent a causal effect of temporary contract on workers' wages exists along the whole wage distribution. I then compare quantile treatment effect parameters with quantile regression coefficients estimated by the procedure used by Koenker and Basset (1978), to asses how much of the wage penalty can be imputed to a price effect and whether also a composition effect caused by the peculiar characteristics of the workforce exists.

Considering the Europe as a whole, I find that there exists a wage penalty for temporary workers which decreases along the wage distribution ranging from 21,3 at the 10th percentile to 14,5 at the 90th percentile and that the treatment effect explains the most part of this wage differential and concerns specially low-earning workers.

Deepening the analysis for each country, I see that it is not possible to draw identical conclusion for all of them, but it is necessary to distinguish between Mediterranean and Central and North European countries by virtue of their way of deregulating labor market and of their consequent temporary employment evolution. In countries like Spain and Italy, which experienced the largest drop in the Employment Protection Legislation (EPL) subindex for temporary employment, a strong causal effect induced by temporary contracts exists in the lower tail of the wage distribution, where low-earning temporary workers are subjected to a wage penalty caused by the kind of contract, which is equal respectively to about 12% and 16,5%. In Spain a treatment effect, equal to about 13,4%, which almost totally explains the wage penalty, can be found also in the upper tail of the wage distribution, while in Portugal it is not possible to identify an heterogeneous treatment effect along the wage distribution.

Outcomes differ for Central and North European countries where I can suppose that also the composition of the labor force and the self-selection of workers influence the wage distributions of temporaries and permanents. For the Austrian case it is possible to hypothesize that they affect wages together with the kind of contract, while in Ireland and UK, where there has been no trend increase in the incidence of temporary employment, a wage penalty can be observed only in some percentiles of the wage distribution, but it is not possible to asses the existence of an heterogeneous treatment effect along the wage distribution.

Results here presented show therefore that it is necessary to distinguish between the two components of the wage penalty and to identify the real price effect induced by the kind of contract, in order to detect to what extent and in which countries temporary workers are discriminated compared to the permanent ones further to different reform strategies with respect to Employment Protection Legislation (EPL).

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