Alma Mater Studiorum
Università di Bologna

DOTTORATO DI RICERCA IN
SCIENZE STATISTICHE

CICLO XXX

Settore Concorsuale:	13/D2
Settore Scientifico Disciplinare:	SECS-S/03

Estimating Causal Effects on the Entire Distribution of Wages

An application to italian temporary contracts during the economic crisis

Presentata da: Elisa Iori

Coordinatrice Dottorato:	Supervisor:
Prof.ssa Alessandra Luati	Prof.ssa Pinuccia Calia

Esame Finale Anno 2019

Abstract

Our research question arise from an empirical problem regarding the introduction and spread of new, more flexible, contractual forms in the Italian labour market in the aftermath of the economic crisis. The aim of the work is the decomposition of changes in the distribution of wages using a semi-parametric methodology to estimate counterfactual densities in order to analyse the role of various explanatory factors (composition and discrimination effects). Using data from from Eurostat, the Italian cross-sectional EU-SILC surveys 2007 and 2013, results show that a wage penalty at the bottom of distribution of wages is most important explanations accounting for pay differences between temporary and permanent contracts while changes in the distribution of wages across time are due to the job-polarisation of the labour market in which low paid jobs are the most affected.

Disclaimer: The responsibility for all conclusions drawn from the data lies entirely with the author

Contents

List of Figures

List of Tables

Introdution

In the recent years there has been a growing interest in the evaluation literature for models that are informative on the impact distribution: while regression on the mean gives us only a generic picture, the description of the differences of the impact among the entire distribution of an outcome variable is now considered fundamental: when evaluating the efficacy of social programmes the researchers should investigate not only if a program did or did not work but also how, why and for whom (Imai & Ratkovic, 2013). This research then seeks to contribute to the field of the evaluation of effects among the entire distribution of an outcome variable of interest. Our research question arise from an empirical problem regarding the change occurred in wage distribution of workers and the consequent increase of wage inequalities in the labour market. The introduction and spread of new, more flexible, contractual forms since the early 1990's has contributed to lessen the employment protection legislation in all the European labour markets. In Italy as well a series of measures introduced various kind of flexible contracts. Moreover between 2008 and 2009 a global financial crisis deeply impacted the European Nations in terms of job losses, lack of wage growths and rising inequalities. For these reasons understanding and monitoring changing in the nature of work relationships is crucial to reinforce the present and future quality of life for the workers. The aim of the work is the decomposition of changes in the density of wages using a semi-parametric methodology to estimate counterfactual densities, that has never been implemented for the Italian case. The role of various explanatory factors is analysed to account for the evolution and the differences of wages for temporary and permanent workers. We analyse also to what extent wage inequality has changed in Italy before and after the economic crisis because of the spread of the new contractual forms and changes in the wage structure. This study is based on data from Eurostat, the European Union-Survey on Income and Living Conditions (EU-SILC) 2007 and 2013 cross-sectional waves, to cover the periods before and after the crisis. In the first Chapter we present a review of the most recent techniques to evaluate effects among the entire distribution of an outcome variable of interest. In the second Chapter we will introduce the economic framework describing the reforms and trends that characterized the evolution of the Italian labour market. The third Chapter is dedicated to the description and implementation of the semi-parametric technique used to estimate the counterfactual distributions. Results and conclusions of the analysis are presented in the fourth and last Chapter.

Disclaimer: The responsibility for all conclusions drawn from the data lies entirely with the author

Chapter 1

Beyond the mean

1.1 Introduction

The traditional approach to social program evaluation has been centred on estimating mean impacts. According to Heckman et al. (1997) the case for using the mean to evaluate a programme is funded upon two key conventions: the first is that an increase in the total output increases welfare, and the second is that undesirable distributional aspects of programmes are either unimportant or are somehow compensated. However they discuss that both of these assumptions are unlikely to be realized in reality as many programme-driven changes cannot be redistributed or condensate to produce a measure of total welfare and they prove indeed that heterogeneity in response to programmes is empirically relevant (Heckman et al., 1997). Since this seminal work the scope of the analysis of the distribution of an outcome variable, i.e. to explore what are the differences in the response of people to a programme, has been a topic of intense research in the last decade. Treatment effect heterogeneity is defined as the degree to which treatments have different (causal) effects on each unit. In other words the researchers should infer how treatment effects vary across individual units and/or how causal effects differ across various treatments (Djebbari & Smith, 2008). Indeed, the estimation of such important differences should play an essential role in selecting the most effective programme, finding sub-populations for which a treatment is effective or harmful and generalizing causal effect estimates obtained from an experimental sample to a target population (Imai & Ratkovic, 2013).

A first method to represent heterogeneity of impacts in terms of observables is already allowed for in the linear regression framework: indeed it is possible to identify subgroups for which the mean impact could be different, adding interaction terms between the intervention and observables (Ravallion, 2009). However this technique may miss some important dimensions of heterogeneity. As noted by some authors (Jackson & Page (2013), Bitler et al. (2006) and Heckman et al. (1997)) if within-group variation exceeds across-group variation in mean impacts, subgroup analysis may fail to capture important differences in treatment effects and this kind of evidence could be decisive in making relevant decisions regarding interventions aimed at reducing inequalities. Moreover not all sources of heterogeneity are observable so another approach in the linear framework would be to allow for latent heterogeneity using a random coefficient estimator[1]. However in the contest of evaluation, looking at subgroup variation in treatment effects basically allows an assessment of the efficiency of actual and potential targeting rules, while estimation of the extent of variation in impacts not related to observables may show the need for data collection to be improved (Djebbari & Smith (2008), Angrist (2004)). Knowledge about how program impacts vary, and how they relate to untreated outcomes give information on how inequality is affected by programmes which is the most interesting and useful thing in this context (Khandker et al., 2009). We begin this first Chapter presenting a review of the recent evaluation literature dedicated to methods for assessing heterogeneous treatment effects on distributions.

1.2 A Statistical Approach to Evaluation

The fundamental aspect of the programme evaluation problem is that one can not simultaneously observe an individual receiving a treatment from a programme and not receiving it. The concept of counterfactual is then introduced to picture different hypothetical states of the world or outcomes. In fact to allow for causal interpretation of impacts, the comparison between outcomes should be setted in a way that only the presence or absence of the treatment varies across the states, holding all other factors constant (Heckman, 2008). Defining and estimating a proper counterfactual is therefore the central focus of statistical methodology in this field. In the simplest form of the evaluation problem, every

[1]Applying this type of estimator to the evaluation data for PROGRESA, Djebbari & Smith (2008) find that they can convincingly reject the common effects assumption in past evaluations.

individual i can present one of two mutually exclusive states of the world described by a binary random variable $D_i = \{0, 1\}$ where 0 represent the untreated (or non-participant) state and 1 the treated (or participant) state. A potential outcome for each individual Y_i is linked to each state:

$$\text{potential outcome} = \begin{cases} Y_i^1 & \text{if} \quad D_i = 1 \\ Y_i^0 & \text{if} \quad D_i = 0 \end{cases}$$

Unfortunately, as stated before, only one outcome is observable for each person and this relation is summarized in the following well-known equation, the Neyman-Rubin Model (Rubin (1972),Rubin (2005)):

$$Y_i = Y_i^0 \cdot (1 - D_i) + Y_i^1 \cdot D_i$$

In other words Y_i^0 is the outcome of an individual that has undergone a treatment, while Y_i^1 is the individual's outcome had s/he experienced the programme (Imbens & Wooldridge, 2009). The measure of the difference between Y_i^0 and Y_i^1 can then be considered the causal effect of the treatment for individual i and it the primary interest of the researcher.

It is now possible to set a first definition of causal impact (α) that doesn't require any further specification or assumption. It is simply the difference between the two potential outcomes, namely between what can be observed in the presence of the treatment, the factual, and what could be observed without it, the counterfactual:

$$\alpha_i = Y_i^1 - Y_i^0$$

Comparing the potential outcomes for each individual is of course impossible and Holland (1986) defined it the "fundamental problem of causal inference". Traditionally this problem has been overcome by the identification of the average effect on a target population or group of people, assuming the effect would be constant for all individuals or, at most, assuming heterogeneity for sub-groups of population. One measure of interest is the average difference between a randomly selected group of individuals that experience a treatment and another randomly selected group of untreated individuals. This quantity is better known as the Average Treatment Effect (ATE) which represents the expected value of the effect for a generic individual randomly selected (Xie et al., 2012):

$$E(\alpha) = E(Y^1 - Y^0) = E(Y^1) - E(Y^0)$$

Since ATE is defined for the whole population, it is not very useful for evaluation purposes. More often it is better to identify the treatment effect for a defined sub-population, usually the one composed by recipients, and this measure is defined as the average treatment effect on the treated (ATT):

$$\alpha_{ATT} = E(\alpha|D=1) = E\left[Y_i^1 - Y_i^0|D_i=1\right] = E\left[Y_i^1|D_i=1\right] - E\left[Y_i^0|D_i=1\right]$$

with the second term corresponding to the counterfactual. Estimation of this quantity often involves the comparison in time of the same group of treated to avoid time variation bias, comparison between different groups of people to avoid selection bias, or a combination of both (Imbens & Angrist, 1994).

However,since there is likely to be a distribution for both Y_i^1 and Y_i^0 in the population, it is more realistic to move beyond the mean and to think that the treatment effect is different for different people. It would be more accurate then to construct the outcome distribution for both participants and non-participants to better evaluate all the implication of a program. Unfortunately this of course brings along more complications than the estimation of the single mean (Heckman et al., 1999).

The cumulative distribution for a random variable Y_d evaluated at y can be defined as the probability that Y_d will take a value less than or equal to y:

$$F_{Y_d(y)} = Pr(Y_d \leq y) = E[1(Y_d \leq y)]$$

In the simplest case, a true experiment with of random assignment, $F_{Y_1}(y)$ and $F_{Y_0}(y)$ are easily identified:

$$F_{Y_1}(y) = E[1(Y \leq y)|D=1]$$
$$F_{Y_0}(y) = E[1(Y \leq y)|D=0]$$

Thus we can give a first, very general definition of the distributional treatment effect as the difference between the distribution of the outcome for the treated population and the distribution of the outcome for the untreated population:

$$DTE(y) = F_{Y_1}(y) - F_{Y_0}(y)$$

From the identification of $F_{Y_1}(y)$ and $F_{Y_0}(y)$ it follows the identification of any function of these marginal distributions like quantiles. Since they have a natural and intuitive interpretation they were greatly exploited in the development of this brunch of literature.

1.3 The Quantile Regression

A first powerful tool to look into the distribution of an outcome variable is the quantile regression model introduced by Koenker & Bassett (1978) and subsequently highly developed and exploited[2]. Quantile regression models seek to extend the idea of quantiles (the division of reference population into segments of equal proportion) to the estimation of models in which the quantiles of the conditional distribution of the response variable are expressed as functions of observed covariates (Koenker & Bassett, 1978). Intuitively the philosophy beneath quantile and conventional regressions is a lot alike: adding covariates can capture confounding factors, interaction terms, likewise mean regressions, identify sub-groups effects and instrumental variables methods have been developed as well to estimate causal effects on quantiles when selection-on-observables assumption is not valid (Angrist & Pischke, 2009). We start the discussion reminding that, since the conditional expectation function (CEF) of a dependent variable Y given a vector of covariates X is the expectation of Y holding the covariates fixed, then the conditional quantile function (CQF) at a fixed quantile τ given a vector of regressors X can be as well defined as:

$$Q_\tau(Y_i|X_i) = F_Y^{-1}(\tau|X_i) = \inf\{y : F_Y(y|X_i) \geqslant \tau\} \tag{1.1}$$

where $F_Y(y|X_i)$ is the distribution function for y_i conditional on X_i. Changes in the CQF of Y as a function of covariates show us whether the dispersion in the outcome variable increases or decreases with the covariate of interest or whether their relationship is changing over time, when time is included (Angrist & Pischke, 2009). Keeping the discussion simple, with no loss of generality, we can assume a separable model of the kind:

$$Y_{\tau i} = q(X_i) + \varepsilon_i$$

Like the standard regression models, also the quantiles can be expressed as the solution to an optimization problem as

$$Q_\tau(Y_i|X_i) = \arg\,\min E[\rho_\tau(Y_i - q(X_i))]$$

where ρ_τ is the loss or check function because, when plotted, it looks like a check-mark and it weights positive and negative elements in an

[2] Ashenfelter & Card (2011), Machado & Silva (2013), Angrist & Krueger (1999), Elder et al. (2015), Melly (2005), Powell et al. (2014) and Lamarche (2011), Galvao et al. (2013), Geraci & Bottai (2007) for panel data, just to cite a few.

asymmetrical way:

$$\rho_\tau(u) = 1(u > 0) \cdot \tau u + 1(u \leqslant 0) \cdot (1 - \tau)u.$$

This asymmetric weighting generates a minimand that allows to choose conditional quantiles.
In the general case a linear setting is chosen to describe the relationship between the outcome and the covariates:

$$q(X_i) = X_i^{'} \beta_\tau$$

and sequentially:

$$\beta_\tau \equiv \arg\ \min E[\rho_\tau(Y_i - X_i^{'} b)]$$

This is a linear programming problem that can be solved with standard statistical software (Angrist & Pischke, 2009). So quantile regression allows to estimate different coefficients for each quantile τ in the distribution of the outcome Y conditional on a vector of covariates X. This is a first way to present a program distributional impact by examining the effects for households or individuals across the range of Y. Specifically, the quantile coefficients can be interpreted as the partial derivative of the conditional quantile of Y with respect to one of the regressors, such as program D (Khandker et al., 2009). When the coefficients are equal we are in presence of a so-called "location-shift" effect, meaning that changes in covariates have the same effect all over the distribution and within-group inequality remain fixed. In contrast if coefficient estimates differ across quantiles then changes in the covariates have a different role across the outcome distribution increasing (or decreasing) inequality, changing the variance within groups (Angrist & Pischke, 2009). This is one of the reasons quantile regression methods have acquired an important role in the evaluation process. In fact, since their first appearance, quantile regression models have been used in a great deal of empirical works and this short list is just an example: Buchinsky (1994), Messinis (2013), Lamarche (2011), Jackson & Page (2013), Djebbari & Smith (2008) and Dammert (2008). In empirical economics, one of the motivations under the exploitation of quantile regression models relies in the interest of labour economists to understand inequality in wages distributions (Buchinsky, 1994), particularity in how it changes conditional on specific covariates like education and training (Angrist & Pischke, 2009). The whole conditional wage distribution, estimated by quantile regression methods, can be given a natural economic interpretation since the quantile regression coefficients can be interpreted as rates of return to different characteristics at different points of the conditional wage distribution (Melly, 2005). Quantile regressions capture the impact of changes in covariates upon a conditional wage distribution in very much the same way that mean regression measures the impact of changes in covariates upon the mean of the conditional wage distribution (Machado & Mata, 2005). However, in the evaluation setting is crucial to point out two tricky elements of quantile regression as it has been described so far. First of all quantile coefficients describe changes in the distribution of the outcome but not on individuals, meaning that they describe what happens, for example, to the group at the bottom 10 percent of the distribution in presence or absence of the intervention regardless of the individuals that compose that group. Second, we have described so far only conditional quantiles. On the other hand moving from conditional to marginal quantiles allows us to investigate the impact of changes in quantile regression coefficients on overall inequality and not only conditional on covariates (Angrist & Pischke, 2009). Both of the aspects will be addressed in detail in the next paragraph.

1.3.1 Quantile Regression and Quantile Treatment Effects

The crucial point of every evaluation using a set of regression estimates is whether they have a causal interpretation (Angrist & Pischke, 2009). Like the average treatment effect, a proper counterfactual setting is needed since we don't have information about what position an individual i would have in the untreated distribution, had s/he been placed in the treated one. However if the program is randomized, and the omitted variable bias can be excluded, the quantile treatment effects (QTEs) of a program on a distribution can be calculated as the difference in the conditional outcome $Y|X$ across treatment and control individuals that fall in the quantile τ of $Y|X$. When the program is assigned randomly the QTE is defined as the change in the quantiles of the distribution of the conditional outcome:

$$QTE_\tau = Q_\tau(Y|X, D=1) - Q_\tau(Y|X, D=0) \tag{1.2}$$

As briefly introduced in the previous paragraph, when QTEs are identified they allow to describe the effects on the distribution of the outcome of interest but they do not give information regarding the effects on individual beneficiaries. In fact QTEs cannot identify the distribution of treatment effects (Y^1, Y^0) nor can they identify the impact for individuals at specific quantiles (Jackson & Page, 2013). This is due to the fact that from two marginal distributions (participants and non-participants) it is generally not possible to estimate the joint distribution of outcomes (Y^1,Y^0) that would be necessary to estimate the distribution of impacts Y_i^1-Y_i^0 (Heckman et al., 1997). QTEs can be informative about the impact distribution only when the potential outcomes observed under various level of treatment are comonotonic[3] random variables (Fort, 2012). This strong assumptions is referred as rank invariance of the distribution in the presence and absence of the intervention and describe a situation in which the presence or the absence of a programme does not change the position of individuals along the distribution of the outcome (Fort (2012), Jackson & Page (2013)).

So far we have described QTEs that are conditional on a set of chosen covariates. Unfortunately in the evaluation setting, researchers are more concerned with the effects that a program can have on the unconditional distribution of Y^1 and Y^0 , namely QTEs of the kind:

$$QTE_\tau = Y^1(\tau) - Y^0(\tau)$$

Very intuitively unconditional QTEs could be estimated exploiting the quantile regression model (QR) only in a very specific case i.e. when the treatment is randomly assigned, it can be identified by a dummy and no other covariates are included in the model. Only in this case the coefficient on the treatment variable is numerically equal to QTE as defined in 1.2. This is due to the fact that the law of iterated expectations does not hold for quantiles (Angrist & Pischke, 2009):

$$Q_\tau(Y_i|X_i) = X_i^{'}\beta_\tau \nRightarrow Q_\tau(Y_i) = Q_\tau(X_i)^{'}\beta_\tau$$

This means that when additional control variables are added for identification purposes or just to get more precise estimators, the QR coefficient identifies a conditional QTE on the covariates which has a different meaning from its unconditional counterpart (Fort, 2012). Conditioning on covariates in fact affects the interpretation of the disturbance term, i.e. the variable describing the relative position of an individual in the outcome distribution. Consequently the interpretation of estimates from a quantile regression changes as covariates are added as they shift an observation's placement in the conditional distribution (Fort, 2012). The

[3]Comonotonicity/coutercomonotonicity is defined as the perfect positive/negative dependence between the components of a random vector, i.e. simultaneously non-decreasing/non-increasing in each component. This vector can be represented as an increasing/decreasibg functions of a single random variable (Dhaene et al., 2002).

conditional QTE show the effect for individuals with relatively low/high Y even if their absolute value of Y is high/low. The unconditional QTE on the other hand show the effect on a relatively low/high absolute Y. Usually unconditional QTEs are more relevant to policy analysis as are more useful to make decision and can be estimated without parametric assumptions more precisely than conditional effects. Moving from conditional to marginal unconditional quantiles in a counterfactual setting is an area of active research (Angrist & Pischke, 2009).

1.3.2 Estimation of QTEs

After the description of the general setting we can move to discuss some of the most useful and easily applicable estimation procedures. This collection of estimation methods was originally put together by Frölich & Melly (2010) and implemented in STATA in a unique command. Their intuition is based on the observation that when the treatment variable is a dummy and the other regressors work as controls, a propensity-score type weighting scheme can be used to produce different QTEs, exploiting the QR minimization linear programming properties (Frölich & Melly, 2010). These methods include the four most common scenarios in the evaluation literature: they allow both for exogeneity (or selection on observables) and endogeneity (selection on unobservables) of the treatment and produce both conditional and unconditional QTEs. Koenker & Bassett (1978) propose a method that can estimate conditional QTEs when the treatment is exogenous. When the exogeneity assumption may not hold the instrumental-variable estimator of Abadie et al. (2002) can be used to find conditional QTEs If unconditional QTEs is what the researcher is interested in, it is possible to use the method developed by Firpo (2007)[4] when the treatment is exogenous, and Frölich & Melly (2013) if the treatment is endogenous. The implementation of these estimators (except for the one of Koenker & Bassett (1978)) requires the preliminary non-parametric estimation of a propensity score. We present these techniques following the notation and structure of Frölich & Melly (2010).

Clearly the starting point is the linear quantile regression model for each potential outcome:

$$Y_i^\tau = X_i\beta^\tau + D\gamma^\tau + \varepsilon_i \quad \text{and} \quad Q_{\varepsilon_i}^\tau = 0$$

where i are the individuals and D is the treatment dummy. $Q_{\varepsilon_i}^\tau$ is the τth quantile of the unobserved random variable ε_i. β^τ and γ^τ are the

[4]Others may be Frölich (2007) and Melly (2005)

unknown parameters of the model where γ^τ is the conditional QTE at quantile τ. Starting with the simplest case, it is assumed that both D and X are exogenous and selection on observables is a valid assumption that makes the model identifiable:

$$\varepsilon \perp (D, X)$$

The model-linearity assumption, together with the selection on observables assumption imply that:

$$Q^\tau_{Y|X,D} = X\beta^\tau + D\gamma^\tau$$

meaning that we can estimate the unknown parameters from the joint distribution of Y, X and D which are all observable from the data. The unknown coefficients can thus be estimated by the classical estimator of Koenker & Bassett (1978)

$$\begin{aligned}(\hat{\beta}^\tau, \hat{\delta}^\tau) &= \text{argmin} \sum \rho_\tau(Y_i - X_i\beta - D_i\gamma) \\ &= \text{argmin} \sum W_i^{KB} \times \rho_\tau(Y_i - X_i\beta - D_i\gamma)\end{aligned}$$

where W_i^{KB} are all equal to 1 and γ^τ is the conditional QTE from an exogenous program. The second line of the equation is needed to illustrate the connection with the other estimators we are considering.

Since very few studies arise from randomized experiments, many applications deal with a treatment D potentially endogenous and require an instrumental variable (IV) identification strategy. The presence of a valid instrument Z is then necessary alongside the dummy treatment variable D_z to estimate QTEs. Below we report the standard assumptions required for IV models, i.e. monotonicity (the non-existence for defiers) and a conditional independence assumption on the IV:

$$\begin{aligned}&(Y^0, Y^1, D_0, D_1) \perp Z|X \\ &0 < Pr(Z = 1|X) < 1 \\ &E(D_1|X) \neq E(D_0|X) \\ &Pr(D_1 \geq D_0|X) = 1\end{aligned}$$

Individuals with $D_1 \geq D_0$ are referred to as compliers[5] and treatment effects can be identified only for this group. Abadie et al. (2002) show in

[5]We refers as compliers the sub-population that is induced by the instrument to change the value of the endogenous regressors (Imbens & Wooldridge, 2009)

their work that the conditional QTE γ^τ for compliers can be consistently estimated by this version of a weighted quantile regression:

$$(\hat{\beta_{IV}^\tau}, \hat{\gamma_{IV}^\tau}) = \text{argmin} \sum W_i^{AAI} \times \rho_\tau(Y_i - X_i\beta - D_i\gamma)$$
$$W_i^{AAI} = 1 - \frac{D_i(1-Z_i)}{1-Pr(Z=1|X_i)} - \frac{(1-D_i)Z_i}{Pr(Z=1|X_i)}$$

$Pr(Z=1|X_i)$ needs to be preliminary estimated, which can be obtained with traditional models like probit or logit[6]. The two estimators presented above focused on conditional treatment effects.

Now we move to the two methods that allow to estimate unconditional QTEs while using covariates only for identification and to increase efficiency. The covariates X are included in the first-step estimation of the probit model and then integrated out thanks to the weighting scheme in order to produce an estimation of the effect that is not a function of the covariates any more. In the case of unconditional endogenous QTE Frölich & Melly (2013) proposed an estimator with the following weighting scheme:

$$(\hat{\alpha_{IV}^\tau}, \hat{\Delta_{IV}^\tau}) = \text{argmin} \sum W_i^{FM} \times \rho_\tau(Y_i - \alpha - D_i\Delta)$$
$$W_i^{FM} = \frac{Z_i - Pr(Z=1|X_i)}{Pr(Z=1|X_i)\,[1-Pr(Z=1|X_i)]}(2D_i - 1)$$

To make a quick comparison, both the weights W_i^{AAI} and W_i^{FM} are created to identify the compliers, but only the latter has the property to balance the distribution of the covariates between the treated and non treated compliers (Frölich & Melly, 2010). $Pr(Z=1|X_i)$ can be preliminary estimated with a probit or logit model.

Finally we consider the case where the QTEs are unconditional and the treatment is exogenous conditional on X. The assumption that the support of the covariates is the same independently of the treatment is required because in a non parametric model the conditional distribution outside the support of the covariates cannot be defined:

$$(Y^0, Y^1) \perp D|X$$
$$0 < Pr(D=1|X) < 1$$

The estimator proposed by Firpo (2007) is then the following:

$$(\hat{\alpha^\tau}, \hat{\Delta^\tau}) = \text{argmin} \sum W_i^F \times \rho_\tau(Y_i - \alpha - D_i\Delta)$$
$$W_i^F = \frac{D_i}{Pr(D_i=1|X_i)} + \frac{1-D_i}{1-Pr(D_i=1|X_i)}$$

[6] Optimization problems can arise since some of the weights can be negative and produce a non convex situation (Abadie et al., 2002).

This is a traditional propensity-score weighting estimator or inverse probability weighting where $Pr(D = 1|X_i)$ is estimated with a probit or logit model. The coefficients for the variable D obtained with these estimation procedures, represent the QTEs of the programme.

Another set of methods developed in the literature to estimate heterogeneous impacts on a distribution of an outcome, has relied on a different approach even though it refers again to the estimation of quantile coefficients and the linear relationship assumption between the outcome and the covariates. Machado & Mata (2005) for example estimate quantile coefficients of the conditional wage distribution using Koenker & Bassett (1978) quantile regression then use re-sampling non parametric algorithm to estimate both the real and the counterfactual unconditional distribution using different re-weighting schemes. Also Melly (2005) estimates a conditional wage distribution by quantile regression and then integrate out covariates to obtain unconditional quantiles like Machado & Mata (2005) but he extends the method solving the problem of crossing of different quantile curves and by determining the asymptotic distribution of their estimator. Firpo et al. (2009) instead run a regression of the re-centered influence function (RIF) of the unconditional quantile on the explanatory variables to estimate parameters that capture changes in unconditional quantiles in the presence of exogenous regressors. It is worth noting then that Quantile Regression approach has been very important in the evaluation setting to develop methods for the estimation of counterfactual settings allowing empirical analysis to look for heterogeneous effects over a whole distribution. On the other hand this methods present some drawbacks, like the linear assumption between the outcome and the covariates and the fact that from quantile coefficients it is not possible to reconstruct other statistics of the distribution. Both of these limitations are overcome by the following set of methods.

1.4 Distributional Treatment Effects

So far we have focused on the quantile function $Q_Y(\tau)$ and its parameters. However in order to evaluate treatment effects on distributions it is possible to work on either the quantile function $Q_Y(\tau)$ or the distribution function $F_Y(y)$ since one is the inverse of the other as shown in Eq.1.1. The natural estimator for the distribution function is of course the empirical distribution function:

$$\hat{F}_Y(y) = \frac{1}{n}\sum_i 1(y_i \leqslant y)$$

from which the quantile function $Q_Y(\tau)$ can be derived:

$$\hat{Q}_Y(\tau) = inf\{y|\hat{F}_Y(y) \geqslant \tau\}$$

since the quantile function is invariant to monotone transformations. In this very simple non-parametric case, estimating one or another is clearly the same. Unfortunately almost certainly empirical problems require assumptions and parametric models. When this happen modelling the QF or the CDF is a different procedure and another brunch of literature is required. In this paragraph we will present a short review of this alternative methodology even though some parallelisms can be done: like quantile estimators we may not want to work with conditional distributions even when we need covariates for identification. The solution would be then to estimate the conditional distribution and then integrate it out to obtain the unconditional one:

$$F_Y(y) = f(y;x) = \int_{x\in\Omega_x} F(y|x)dF(x)$$

With this notation it is easy to see that a policy or an intervention can affect the distribution of the outcome of interest in two different ways: changing the distribution of the covariates $F(x)$ or changing the relationship between the outcome and the covariates represented by the conditional distribution $F(y|x)$. To asses either changes a counterfactual exercise is required (Chernozhukov et al., 2013). To be more clear, let's introduce the empirical setting we will be using later on. Suppose we would like to analyse the wage differences between two group of workers and to asses the impact on these distributions of the type of contract they are subjected. Given a dummy variable $D = \{0,1\}$, let 0 denote the population of workers with a permanent contract and 1 denote workers with a temporary job. Y_d denotes wages and X_d denotes job marked-relevant characteristics that affects wages for population d. Let $F_{Y_d|X_d}(y|x)$ be the generic conditional distribution for Y_d, where $F_{Y_1|X_1}(y|x)$ and $F_{Y_0|X_0}(y|x)$ represent the observed conditional distribution functions of wages for temporary and permanent workers respectively. In this context the counterfactual distribution $F_Y^c(y)$ can be defined as the distribution function of wages that would have prevailed for permanent workers had they faced temporary workers wage schedule $F_{Y_1|X_1}$:

$$F_{Y_1}^c(y) = F_{Y_1|X_0}^c(y|x) = \int F_{Y_1|X_1}(y|x)dF_{X_0}(x) \tag{1.3}$$

This distribution is constructed by integrating the conditional distribution of wages for temporary workers with respect to the distribution of characteristics of permanent workers. The methods we are going to briefly present can rely on manipulation of the conditional distribution or the distribution of the covariates (Fortin et al., 2011). The counterfactual distributions can be estimated both with regression-type techniques or with semi-parametric reweighing methods and both are correct and well performing. They also produce same results when one uses a saturated model to calculate the propensity score and the regression is conditional on the same covariates (Melly (2005), Chernozhukov et al. (2013)). To be able to give a causal interpretation for these effects we need to add more assumptions as we are going to discuss since this will be the approach on this work. One of the reasons relies on the fact that it allows a decomposition exercise which has been proven very useful in analysing wages.

1.4.1 Decomposition Methods

The kind of counterfactual that we have just defined is the key ingredient of the decomposition methods often used in applied economics[7]. Typically a great deal of questions regarding wages and how they change for subgroups (like temporary and permanent contracts) and in time are answered using decomposition methods aimed at quantifying the contribution of various factors. Starting with the seminal papers of Oaxaca (1973) and Blinder (1973) this methods has become a standard tool kit for labour economics. The Blinder-Oaxaca decomposition is a parametric, linear decomposition of the mean difference:

$$\begin{aligned}\overline{Y}_1 - \overline{Y}_0 &= (\overline{X}_1\beta_1 - \overline{X}_1\beta_0) + (\overline{X}_1\beta_0 - \overline{X}_0\beta_0) \\ &= (\beta_1 - \beta_0)\overline{X}_1 + (\overline{X}_1 - \overline{X}_0)\beta_0\end{aligned}$$

where the total mean difference is decomposed in the effect of changes in the characteristics of the two groups and the effect of changes in the coefficients, or the unexplained part. The original method proposed by Oaxaca and Blinder has been improved and expanded upon over the years and the most important development has been the extension of the decomposition methods to distributional parameters other than the mean (Fortin et al. (2011), Chernozhukov et al. (2013), DiNardo et al. (1996), Machado & Mata (2005), Autor et al. (2005)). Subsequently

[7] Magnani & Zhu (2012), (Elder et al., 2010), Biewen & Jenkins (2005).

the difference in the observed wage distributions described above can be decomposed as:

$$F_{Y_1|X_1} - F_{Y_0|X_0} = \left[F_{Y_1|X_1} - F^*_{Y_1|X_0}\right] + \left[F^*_{Y_1|X_0} - F_{Y_0|X_0}\right] \tag{1.4}$$

where the first term in brackets is a composition effect due to differences in characteristics between the two groups and the second term represents unexplained differences which, in the context of labour market, are traced back to changes in the wage structure. This new set of methods are well suited to explore the rising in inequalities of incomes and wages that occurred in the developed countries in the last decades since, once the counterfactual distribution is estimated, the decomposition can be applied to all functions of the distributions, including quantiles and, for example, Gini coefficients. This is one of the advantages that induced us to use this methodology. They can be divided in methods based on manipulation of the conditional distribution or of the covariates distribution defined in Eq.1.3. They can also be divided regarding how much parametric the approach is. Chernozhukov et al. (2013) provides an estimation and the inference procedure for a regression method applied to the conditional distribution of the outcome. Inspired by the hazard model suggested by Donald et al. (2000), they use a distribution regression method where the link function is a Logit model for each value of y to obtain the distribution for one group. Then the counterfactual distribution is obtained averaging. An unrestricted non-parametric estimator (they used simply the empirical distribution function) is used for the covariates distribution. They obtain uniformly consistent and asymptotically Gaussian estimators. Also the methods proposed by Machado & Mata (2005) and Melly (2005), described before, can be considered in this group of methods, but with linear quantile regression. In fact they both compare the two marginal distributions, the real and the counterfactual, to obtain the wage structure effect and compute the composition effect by difference with the overall change. However, as noted before, with the estimation of coefficients it is not possible to calculate other statistics of the distribution. Magnani & Zhu (2012) combine the mean decomposition method by Fortin (2008) with the unconditional quantile regression by Firpo et al. (2009) to decompose gender wage differential at different quantiles. On a total different approach DiNardo et al. (1996) do not take into account the conditional distribution but estimate directly both the marginal and the counterfactual with a semi-parametric procedure closer to the reweighting schemes seen in the beginning of the chapter. This is the method that we decided to exploit for our empirical application. Its peculiarities and how it has been adapted to the Italian case will be described in Chapter 3. Generally speaking it is possible to say that one of the advantages of the re-weighting approach is that it does not assume any functional form for the relation connecting the covariates to the distribution of the outcome and is one of the reasons it was chosen.

To conclude it is worth noting that one difference between decomposition exercises and proper programme evaluation is that the composition effect is a key component of interest for the former, while it is a selection bias resulting from a confounding factor to be controlled for in the latter. On the other hand the residual factor is what concern the most the evaluator since, under proper independence assumptions, can represent a measure of the impact of a programme. In our example the residual factor can be seen as a wage penalty imputable to the type of contract. As pointed out by Fortin et al. (2011), a second limit regards the fact that these methods are useful to shed light on how much each factor accounts in the changes in the outcome variable but they may not clarify the mechanisms underlying the relationship between factor and outcomes. That means that are useful in indicating which explanation is to be explored in more detail but not how this explanation work. The literature on inequalities is developing in this sense, since the disentangle of the differences can give a more structural interpretation on the decomposition. In the following Chapter we will introduce the empirical problem that is at the base of this work.

Chapter 2

Recent Developments for the Labour Market

2.1 Introduction

As anticipated before, the initial idea around this work deals with an empirical evidence: since the early 1990's Italy underwent a drastic process of reforms concerning the regulation of working agreements that deeply changed the structure of the labour market. Just a little after, the biggest economic crisis of recent history stroke, bringing along long-term consequences especially for the Mediterranean countries in the Europe zone. What are the implications of these two major events on the distribution of salaries is still a topic of research, not only in Italy but in Europe as well. Indeed policy-makers and labour economists have been wildly concerned with changes in wage distributions, raising inequalities, and the effects of changes in the structure of the labour market. In this Chapter we will present a brief introduction of the economic context and describe the reforms and trends that have characterized the evolution of the labour market, especially for Italy. Some explicative cases are presented as well. The aim is to better understand the framework around which the evaluation of both temporary contracts and economic crisis effects is presented later.

2.2 Institutional reforms and the Labour Market

According to Boeri (2011) labour market institutions are defined ”as the systems of laws, norms or conventions resulting from a collective choice, i.e. a by-product of the political process”. They provide incentives or limitations to influence individual choices over labour and payments, impacting on the structure of labour markets. Institutional reforms are consequently defined as changes in the institutions settings that can potentially affect the structure of markets (Boeri, 2011). Indeed one of the biggest reform, and object of primary interest in this research, that took place all over Europe since the beginning of the 1990's has been the process of ”flexibilisation” of the labour market through the progressive spread and deregulation of temporary working agreements. These reforms are mainly partial, meaning that they are introduced with a phasing-in method that affects only a subset of the population. Thanks to these characteristics we can fit in a recent trend in the literature that has been evaluating the effects of labour market institutions on wages, exploiting this kind of reforms as natural experiments (Boeri, 2011).

2.2.1 Job insecurity and Structural Factors

In comparison with other European countries, Italy was a latecomer in the process of ”flexibilisation” of the labour market trough institutional reforms[1] (Bolelli, 2017). However according to the Employment Outlook of OECD of 2004 (OECD, 2018a), after more then ten years of reforms, our country had relaxed national employment protection legislation more than other countries. Indeed the process started in the early ninety's and reached its peak in 2014 when the reform, known as Jobs Act, introduced a lighter dismissal regime for future long-term contracts, and reduced the sanctions on collective and unfair dismissal procedures (Bolelli, 2017). Generally speaking the tool used to increase flexibility and deregulation in the market has been the introduction in the legislation of non-standard, temporary contracts. This strategy contributed to create a double-tier regime in which only standard workers saw their protection legislation remaining almost intact. Indeed flexibility was introduced into the Italian system by the margins (Commission, 2006b). The new working arrangements allow employers to bypass the strong labour protection legislation and collective bargain of permanent con-

[1] Labour market flexibility is defined as the capability to respond to changes in market conditions, like supply and demand or wage rate (Boeri, 2011).

tracts, saving on wages and social security obligations[2] (Bolelli (2017), Ballestrero & De Simone (2012)). This process of liberalization of working arrangements in the spirit of flexibility consequently increased the precariousness of workers since a growing number of them were excluded from social rights and employment protection. (McKay et al., 2012). The increase in flexibility also implied a gradual loss of power by unions since temporary contracts prevent them to control over conditions in new agreements and employers right. For example the reforms gradually decreased the power of collective bargaining by marginalizing their role in the decisions concerning the use of non-standard contracts inside the firm, in challenging the application of a temporary contracts or in advocating for the permanent hiring for temporary workers (Bolelli (2017), Ballestrero & De Simone (2012)). This progressive erosion of labour power though is not only attributed to labour legislation reforms but it is also attributed to structural factors like the harshness of the economic crisis that hit with a negative impact on working conditions (European Parliament(2016), Bolelli (2017)).

The Great Recession was trigged by a financial meltdown and from the United States it spread all over the world. It has proven to be the worst in intensity and length since the Great Depression of 1929 and, because of its consequences, it reminded the researchers how deeply important and complicated is the behaviour of labour markets over the business cycle (Elsby et al., 2016). Indeed M. Andersen (2011) studied how labour markets characterised by flexibilisation can cope with the consequences of the Great Recession finding out that short term unemployment constitutes a relatively large share of overall unemployment in comparison to long-term unemployment but this must be associated with social safety net and active labour market policies with some concerns for the efficiency of the system in the long run. Bentolila et al. (2012) found out that Spain, whose labour market is characterised by high levels of temporary contracts and light employment protection legislation, could have avoided about 45% of its unemployment surge had it

[2]From a business perspective, such arrangements may provide attractive flexibility. From the perspective of workers, they may offer paid employment to some who would otherwise be unemployed and appeal to others who do not want to be tied down to a rigid work schedule, yet also may lack many of the benefits and protections afforded by traditional jobs. Employment rights and protections refer to statutory minimum standards of employment such as minimum wage, overtime pay, hours of work limits, public holidays, paid vacations, notice of termination, and job protection for maternity or parental leave.

adopted French more strict employment protection legislation. Arpaia & Curci (2010) point out also that the negative effects of the Recession have hit harder some socio-economic groups: males, workers with weaker contract agreements, less skilled, members of ethnic minorities and the young. In the light of these findings it seemed foremost important to evaluate the effects of the job market structure, especially the new type of employment legislations, and specific personal characteristic to quantify the determinants of this heterogeneous response to the crisis, focusing in particular on effects on wages. Indeed policy makers and labour economists have been really concern also with changes in the wage distribution and inequality occured during and after the economic crisis and the implications of the new institutional reforms.

2.3 Recent Topics on Wage Inequalities

Literature on evaluation of wage inequalities grew systematically in the last decades motivated initially by the increased interest on the topic in the United States occurred at the beginning of the 1980's. Europe as well has faced a similar pattern but with many peculiarities for each state. Typically explanations have been looked for in changes in the structure of the labour market, like the institutions described above, or in changes in the characteristics of the workers, or a combinations of both. For example Gosling et al. (2000) used U.K micro-data to describe the increase in education differentials for males and a rise in within-group dispersion. Both DiNardo et al. (1996) and Chernozhukov et al. (2013) applied their methodology to study the evolution of U.S wage distribution during this period. They both stressed the role of de-unionisation, but DiNardo et al. (1996) found that also shocks on supply and demand were main factors in explaining inequality, while Chernozhukov et al. (2013) insisted more on the decline of the minimum wage. Moreover Angrist & Pischke (2009) stated that inequality in the U.S. has been growing asymmetrically in recent years, particularly for what concerns returns of education. A large group of recent works studied the implications of new technological changes on wages as a possible explanation for raising inequalities and job polarisations is one of the most popular theories beneath. Job polarisation is defined as a shift in employment from middle to low and high income workers, with the average wage growth slower for middle-income workers, higher for both extremes (Barany & Siegel, 2015). In fact a rising body of literature has been inspecting the relationship between distribution of wages and job polarisation. Acemoglu & Autor (2011) built a model for skill demand and wage determination and found out that over the last three decades in U. S. it is possible to observe a substantial decline in real wages for low skill workers, men in particularly, a non-monotone change in earning levels in different parts of the earning distribution, and a job polarization of the market with increases in employment in high skill and low skill occupations in comparison to middle skill occupation. They suggest that a rapid diffusion of new technologies directly substitutes capital for moderately skilled workers. Regarding Europe also Goos et al. (2014) state that declines in routine intensive employment positions caused by changes in technology are the most important factor in the rising of job polarisation. It is in fact generally accepted among economists that this particular structure depends on the current relationship between workers' skills and technological progress but how this works is still a source of debate (Katz & Autor (1999),Goos & Manning (2007)). The theory that has been developed to explain the driving force behind job polarisation is called task-biased technological change: job tasks, depending on their characteristics are impacted by technology improvements in different ways. According to this theory, middle-skilled workers are assigned to routine tasks which are highly at risk to be replaced, while the remaining two sub-categories with non routine tasks (manual for low-skilled, intellectual for high-skilled) are expanding since technological changes cannot replace them. In contrast, another theory regarding structural changes in the recent history regards the so called "upgrading of occupation" (Card & DiNardo (2002), Goldin & Katz (2007)) and is explained by a skill-biased technological change where only the highly skilled workers manage to benefit from technological improvements. Castellano et al. (2017) explore how both these structural changes affect wage inequality in France (for upgrading of occupations), Germany (for job polarisation), and Italy (where neither of the two phenomena can be clearly identified by the authors). Regarding France and Germany, the main results highlight how the endowment effect plays a key role in decreasing or, at least, not increasing wage inequality, whereas in Italy the rising inequality may be due to the wage structure (a lower efficiency of the country labour market in creating better job opportunities and higher-salaries for employees are suggested as explanations). On the other hand Garofalo et al. (2018), investigating the comparative effects that the Great Recession had on the structures of southern European labour markets and wage inequalities, found that the capacity of the Italian labour market in rewarding individual characteristics makes the country less unequal than Greece, Portugal and Spain. In fact the differences on inequalities between these states are explained mostly by the different market structures and their different abilities to reward skills.

Another source of wage inequality that has been inquired intensively in the last years is the wage gap in salaries that may occur between different group of workers like males and female, or white respect to non-white workers. McDonald & Thornton (2011), Kunze (2005), Bhalotra & Manuel (2018), Colella (2014) and Kim (2010) are just some examples.

In the context of this work, we are particularly interested in the previous little literature that inquiry the wage gap for temporary workers especially for the Italian context where this major reform took place as explained above. Santangelo (2011) evaluates whether temporary contracts suffer a wage penalty comparing European countries in the context prior of the Great Recession using data from 2007 and the method proposed by Firpo (2007). She found a wage penalty raging from 13,4% and 7% regarding especially low-earning workers. Comi & Grasseni (2012) and Bosio (2013), using different approaches find equal results. The first use a QR model of Koenker & Bassett (1978) while the latter relaxes the assumption of exogenity for temporary contracts and uses the approach of Frölich & Melly (2013) using the staggered implementation of the reforms as instrumental variable. Both of the works suggest the idea that temporary contracts have increased a segmentation of the labour market in two groups, one with permanent, higher paid workers and one composed of badly paid temporary jobs in which low-skilled and young workers are segregated in. Unfortunately these studies refer to the period prior the crisis so more research is needed to inquiry how the impact of this type of contracts has changed over the years.

2.4 Changes in the Italian Labour Market

Hereinafter some descriptive statistics are presented to show some changes in the Italian labour market occurred between 2007 and 2013, the reference period we choose to include the Great Recession. In Tab. 2.1 is reported in percentage the share of population by activity status, also divided by sub-groups. Generally speaking and not surprisingly,the share of population at work has declined of two percentage points while the percentage of unemployed has risen of almost four points. Between men and women, only the formers saw a decline of the share of working people (-5,5%). Regarding the share of unemployed people, men suffer a bigger increase (6,5% compared with the 1,1% of women) in line with the findings presented in the previous paragraph. Looking at age classes, while unemployment shares have risen of similar amounts for each class (around 4%), it is worth noting that, also in our country, the youngest cohort show the biggest decline in people at work (-10,5%) with the biggest rise in the share of inactive people (6,6%). The oldest cohort present a rise of 8,3% in the share of people at work and a decline of 11,3% in the share of people in retirement showing a change in the retirement scheme. Regarding education, the group with the lowest level of education presents a bigger drop (-7,4%) in the share of working people compared to the other two categories (-4,6% and -2,1% for medium and high education respectively). The same picture appears for the unemployed share, with an increase of 6,2% for lows, a plus 3,9% for medium and 0,5% for high educated people. On the topic of skill levels (where 1 indicates the lower level and 4 the highest one) it is possible to notice that from level 1 to 3 the decline in the share of people at work is little less then -2% while the top level present a much lower decline of -0,7%, suggesting more an upgrading of occupations then a job polarisation-type of change for the structure of the market (Castellano et al., 2017). Unemployment shares also differ: +7,9% for level 1, +6,6% for level 2, +2,4% for level 3 and +1,5% for level 4. Shares of skill-level groups for each year are also plotted in Fig. 2.1.

To give a more complete picture Fig. 2.2 represents the shares of active population by economic activity classified according to the NACE classification (ILO, 2011) for both years. It is possible to notice that the biggest drop is shown in the sectors of Mining and Manufacturing and Constructions.

Given this overview of the economic context and the empirical problem we are dealing with, we shall proceed presenting the methodology chosen and applied to this case.

Table 2.1: Share of Active Population by Activity Status and Sub-groups

Share	2007				2013			
	At work	Unemployed	Retirement	Oth. Inactive	At work	Unemplyed	Retirement	Oth. Inactive
Gender								
Female	44,7%	6,1%	7,8%	41,4%	46,3%	7,2%	5,9%	40,7%
Male	71,4%	5,5%	10,5%	12,6%	65,9%	12,0%	8,0%	14,1%
Age class								
15 - 25	32,8%	9,8%	-	57,4%	22,4%	13,6%	-	64,1%
25 - 35	70,4%	9,8%	-	19,8%	65,9%	14,0%	-	20,1%
35 - 45	76,9%	4,8%	0,3%	18,0%	73,6%	9,1%	0,1%	17,2%
45 - 55	70,4%	4,1%	3,4%	22,1%	70,7%	8,3%	1,3%	19,8%
55 - 65	26,4%	0,7%	46,0%	26,9%	34,7%	4,2%	34,7%	26,5%
Education								
Low	32,5%	3,0%	26,5%	38,0%	25,2%	9,3%	23,2%	42,3%
Medium	59,9%	6,4%	6,4%	27,3%	55,4%	10,3%	5,9%	28,5%
High	77,9%	5,7%	5,0%	11,5%	75,8%	6,2%	3,9%	14,1%
Skills								
Level 1	61,1%	8,8%	13,0%	17,2%	59,5%	16,6%	7,8%	16,0%
Level 2	67,6%	5,2%	12,1%	15,2%	65,7%	11,7%	9,1%	13,5%
Level 3	77,3%	3,8%	9,7%	9,3%	75,7%	6,1%	9,1%	9,1%
Level 4	82,7%	3,0%	9,1%	5,2%	82,1%	4,5%	7,7%	5,7%
Citizenship								
No	57,3%	5,9%	9,6%	27,3%	55,7%	9,4%	7,4%	27,5%
Yes	71,4%	4,6%	0,7%	23,3%	62,1%	11,4%	0,8%	25,8%
Marital Status								
Never Married	54,5%	9,7%	2,4%	33,4%	49,4%	13,8%	1,6%	35,3%
Married	60,3%	3,5%	12,2%	24,1%	60,0%	6,8%	9,6%	23,6%
Was Married	57,4%	5,4%	16,6%	20,6%	59,5%	9,3%	13,5%	17,7%
All population	58,0%	5,8%	9,1%	27,0%	56,1%	9,6%	7,0%	27,4%

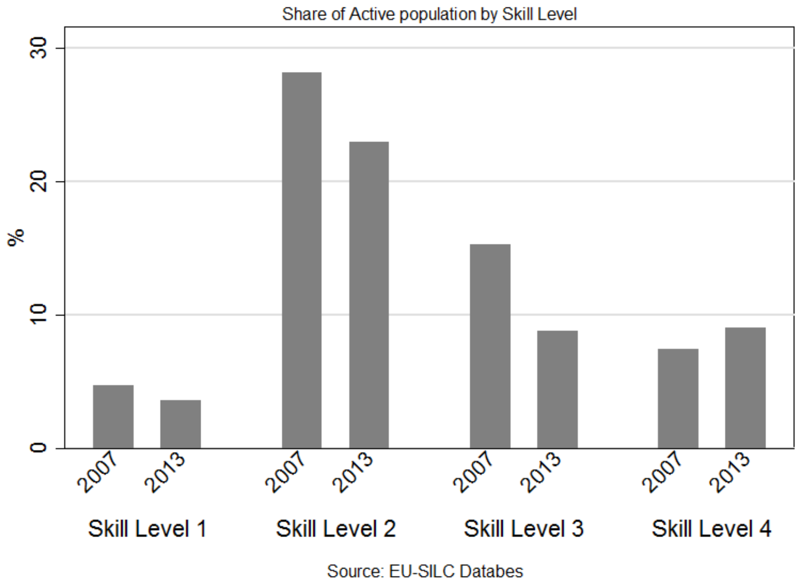

Figure 2.1: Share of Active Population by Skill Level

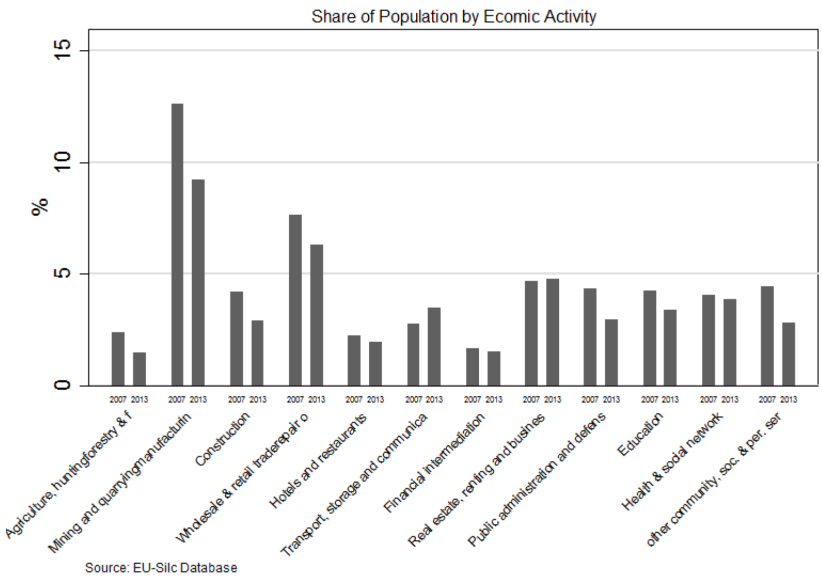

Figure 2.2: Share of Active Population by Economic Activity

Chapter 3

Decomposition of Differences in Wage Distributions

3.1 The counterfactual setting

Following DiNardo et al. (1996) and reconnecting with the first chapter, we can set our framework defining a wage distribution $f(w)$, a set of job-related covariates X and two groups of workers denoted with $D=1$ and $D=0$ where the first one represents workers with a temporary contract, and the second group refers to individuals that work under a permanent agreement. The density of wages for a group of workers, $f_D(w)$, can be written as:

$$\begin{aligned} f_D(w) &= \int_{x\in\Omega_x} dF(w,x,D=d) \\ &= \int_{x\in\Omega_x} f(w|x,D=d)dF(x|D=d) \\ &= f(w_d;x_d) \end{aligned} \tag{3.1}$$

where $f(w_{d=1};z_{d=1})$ and $f(w_{d=0};x_{d=0})$ represent the observed distribution functions of wages and job-related covariates for the two groups. We are interested in the counterfactual density that represents what would be the distribution of wages in the group of workers with a temporary contract if they had the same job-related characteristics of the group of permanent workers. As discussed in the first chapter, this kind of counterfactual is essential to perform the decomposition of the differences in the distributions. The counterfactual density $f^c(w_{d=1};x_{d=0})$

can then be formally written as

$$
\begin{aligned}
& f^c(w_{d=1}; x_{d=0}) = \\
& = \int f(w|x, d=1) dF(x|d=0)
\end{aligned}
\tag{3.2}
$$

We will proceed discussing the assumptions required for the identification of this quantity and the estimation method used in this work.

3.1.1 General Assumptions

To discuss assumption and identification issues we follow the setting and the notation provided by Fortin et al. (2011). Even if it can appear redundant, a first important thing to point out is that we refer to the case where the groups of individuals we are comparing are mutually exclusive [1]:

Assumption 1. Mutually exclusive groups: the population of interest can be divided into two mutually exclusive groups denoted with $D = 1$, for individuals with a temporary contract, and $D = 0$, for individuals with a permanent contract.

From now on the distribution function denoted as $F_{Y_d|D_r}$ will represents the distribution of the potential outcome Y_d for workers in group r that is observed when $d = r$ and counterfactual when $d \neq r$.

Assumption 2. Structural Form: A worker belonging to either group $d = 0$ or $d = 1$ is paid according to the wage structure m_1 and m_0 which are functions of the workers' observables (X) and unobservables (ε):

$$
Y_{1i} = m_1(X_i, \varepsilon_i) \quad \text{and} \quad Y_{0i} = m_0(X_i, \varepsilon_i) \tag{3.3}
$$

where ε_i has a conditional distribution given X $F_{\varepsilon|X}$ and $d = 1, 0$.

The assumption suggests that three sources of variation can produce differences between the wage distributions of the two groups: the wage setting function $m(\cdot)$, the distribution of observables $f_X(x)$ and the distribution of unobservables $f_\varepsilon(\varepsilon)$. The aim of the decomposition in the evaluation literature is to separate the contribution of the wage structure (the treatment effect) from the two others.

[1] Even though most of the empirical literature fall in this case it is important to distinguish with the few cases regarding overlapping groups.

Assumption 3. Simple Counterfactual Treatment: A counterfactual wage structure m^c is said to correspond to a simple counterfactual treatment when it can be assumed that $m^c(\cdot) = m_d(\cdot)$ for workers in group r.

This assumption implies that the alternative wage structure $m^*(\cdot)$ that represents how workers would be paid if there were no temporary contracts does not exist and that we can assume no general equilibrium effects. This is quite an important one and deserve some further discussion especially because of this particular economic context.

3.1.2 Identification

So far we established a general setting. Then we can move to the assumptions that are required for identification in our case:

Assumption 4. Overlapping Support: $\forall X, \varepsilon$ it is valid that

$$0 < Pr[D_g = 1|X = x, E = \varepsilon] < 1$$

This means that both groups of workers have the same set of work-related covariates (this assumption might not be valid for example when one investigates the wage gap between immigrant and citizen workers).

Assumption 5. Ignorability: For $D = \{1,0\}$ let (D_d, X, ε) have a joint distribution. For all x in X, ε is independent of D given $X = x$

$$D \perp \varepsilon | X \tag{3.4}$$

This assumption impose that ε has the same conditional distribution across groups so the difference between a wage distribution and its counterfactual depends solely on differences in the wage structure. In the evaluation literature this assumption is also known as selection on observables.

Proposition 3.1. Identification of Aggregate Decomposition: Under the assumption of simple counterfactual, overlapping support, and ignorability, the overall wage gap can be decomposed in:

$$\Delta_O = \Delta_S + \Delta_X \tag{3.5}$$

where the difference in the wage structure Δ_S reflect the differences between the structural functions $m_d(\cdot)$ and the difference in the distribution of characteristics Δ_X is referred as the composition effect.

When the simple counterfactual and ignorability are satisfied the conditional distribution of Y given X is invariant from manipulations of the marginal distribution of covariates. It follows that equation 3.2 is a proper counterfactual for the distribution of wages that would have prevailed if workers with temporary contracts would have been paid according to the wage structure of permanent ones.

For the purpose of this work we need another assumption:

Assumption 6. Invariance of Conditional Distribution: The construction of the counterfactual wage distribution for workers of group 1 that would have prevailed if they were paid like group 0 workers, assumes that the conditional wage distribution $F_{Y_1|X,D}(y|X=x)$ remains valid when the marginal distribution $F_{X|D_1}$ replaces $F_{X|D_0}$

This holds as it holds 3 and 5 and there are no general equilibrium effects.

3.2 Reweighing Kernel Estimation

Before proceeding with the estimation procedure we need to introduce another statistical tool, the Kernel density estimate $\hat{f}_h$ of a univariate density f based on a random sample $W_1, \cdots, W_n$ of size n with weights $\theta_1, \cdots, \theta_n$ that sum up to one, which can be defined as:

$$\hat{f}_h(w) = \sum_{i=1}^{n} \frac{\theta_i}{h} K\left(\frac{w - W_i}{h}\right), \tag{3.6}$$

where h is the bandwidth and $K(\cdot)$ is the Kernel function. The critical issue in kernel density estimation is the choice of bandwidth Li & Racine (2006). The kernel function used is Gaussian while the weights θ_i are all equal to 1[2]. Actually non-parametric kernel density estimation methods are not new in the study of treatment heterogeneity in a variety of economic fields: Hu & Hibel (2015), Henderson et al. (2006), Henderson et al. (2011), Rothe (2010) and Zhu (2011) are some examples.

3.2.1 A two-term decomposition

DiNardo et al. (1996) prove that the counterfactual density $f(w_{t=1}; x_{t=0})$ can be written in terms of the observable distribution $f(w_{d=1}; x_{d=1})$ with

[2]DFL uses the sample weights multiplied by usual hours of work and normalized to sum to one.

the help of a proper reweighting function to counterbalance the different distribution of covariates in the two groups. More formally:

$$\begin{aligned} & f(w_{d=1};x_{d=0}) = \\ & = \int f(w|x,d=1)dF(x|d=0) \\ & = \int f(w|x,d=1)\psi_x(x)dF(x|d=1) \end{aligned} \tag{3.7}$$

where the reweighting function $\psi_x(x)$ is defined as

$$\psi_x(x) = \frac{dF(x|d=0)}{dF(x|d=1)} = \frac{Pr(x|d=0)}{Pr(x|d=1)} \tag{3.8}$$

Since we are dealing with a ratio of multivariate probabilities that would be difficult to estimate especially when the number of covariates is big, it is useful to apply the Bayes' rule and trace back the quantity to a ratio of univariate probabilities:

$$\psi_x(x) = \frac{Pr(x|d=0)}{Pr(x|d=1)} = \frac{Pr(d=0|x)}{Pr(d=1|x)} \cdot \frac{Pr(d=1)}{Pr(d=0)} \tag{3.9}$$

Both $Pr(d|z)$ and $Pr(d)$ can be easily estimated with a standard Probit model. Once $\hat{\psi}_x(x)$ is estimated it is possible to calculate the counterfactual distribution $f(w_{t=1};x_{t=0})$ applying the reweighting function to the standard kernel estimator:

$$\hat{f}(w_{t=1};x_{t=0}) = \hat{f}_h(w) = \sum_{i=1}^{n} \frac{\theta_i}{h} \hat{\psi}_z(z) K\left(\frac{w-W_i}{h}\right), \tag{3.10}$$

where θ_i are the sample weights, h is the optimal bandwidth and $K(\cdot)$ is a Gaussian kernel.

Since we are interested in decomposing the wage differentials between the two groups of workers we can use the estimated counterfactual and apply the following sequential decomposition:

$$\begin{aligned} & f_{d=1}(w) - f_{d=0}(w) = \\ & = f(w_{d=1}, z_{d=1}) - f(w_{d=1}, z_{d=0}) \\ & + f(w_{d=1}, z_{d=0}) - f(w_{d=0}, z_{d=0}) \end{aligned} \tag{3.11}$$

As discussed in the previous paragraphs, the first line indicates the effect of changes in the job related characteristics, the composition effect, and the second line the residual factors or discrimination effect which correspond to the causal effect of this kind of precarious contracts on the structure of salaries.

3.2.2 A Comparison Over Time

Since 2008 has been a dramatic turning point for the world economic system it is important to to expand the analysis of wage differentials between the years before and after the economic crisis. We now consider two new group of workers and consequentially two distribution of wages $f_{2013}(w)$ and $f_{2007}(w)$. We are now interested in a counterfactual of the kind "What would the density of wages have been in 2013 if workers' attributes had remained at their 2007 level?". In this scenario workers' attributes are represented by a vector $z = (d,x)$ where d is a dummy variable indicating the type of contract and x are other job-related characteristics.

The density of wages at one point in time, $f_t(w)$, can be written as the integral of the density of wages conditional on the set of individual attributes and one date $f(w|z,t_w)$, over the distribution of individual attributes $F(z|t_z)$ at date t_z:

$$\begin{aligned} f_t(w) &= \int_{z\in\Omega_z} dF(w,z|t_{w,z}=t) \\ &= \int_{z\in\Omega_z} f(w|z,t_w=t)dF(z|t_z=t) \\ &= f(w;t_w=t,t_z=t) \end{aligned} \tag{3.12}$$

where Ω_z is the domain of definition of the individual attributes. While $f(w;t_w=2013,t_z=2013)$ represents the actual density of wages in 2013, $f(w;t_w=2013,t_z=2007)$ represents the density of wages that would have prevailed in 2013 had the distribution of individual attributes remained as it was in 2007. Under the assumption that the 2013 structure of wages, which is represented by the conditional density $f(w|z,t_w=2013)$, does not depend on the distribution of attributes, the hypothetical density $f(w;t_w=2013,t_z=2007)$[3] is defined as:

$$\begin{aligned} & f(w;t_w=2013,t_z=2007) = \\ &= \int f(w|z,t_w=2013)dF(z|t_z=2007) \\ &= \int f(w|z,t_w=2013)\psi_z(z)dF(z|t_z=2013) \end{aligned} \tag{3.13}$$

[3]This counterfactual density represent the density that would have prevailed if individual attributes had remained at their 2007 level and workers had been paid according to the wage schedule observed in 2013, since we ignore the impact of changes in the distribution of x on the structure of wages in general equilibrium

where the reweighting function $\psi_z(z)$ is now defined as

$$\psi_z(z) = \frac{dF(z|t_z = 2007)}{dF(z|t_z = 2013)} \tag{3.14}$$

Again equation (3.13) shows that the counterfactual density is identical to the 2013 density except for the function $\psi_z(z)$. Once the estimate $\hat{\psi}_z(z)$ is obtained, it can be used to find the counterfactual density. The difference between the actual 2013 density and its counterfactual density represents the effect of changes in the distribution of workers' attributes. Given our focus on temporary contracts, it would be useful though to account for d and x separately.

Following DiNardo et al. (1996) the density of wages that would have prevailed if temporary contracts, but not other attributes, had remained at their 2007 level is constructed, then a counterfactual where both d and x had remained at their 2007 level is considered. Since the distribution of attributes at one point in time can be written as the product of two distributions:

$$F(z|t_z = t) = F(d|x, t_{d|x} = t) \cdot F(x|t_x = t) \tag{3.15}$$

equation (3.13) can be used to re-write the density of wages in 2013 as:

$$\begin{aligned} &f(w; t_w = 2013, t_{d|x} = 2013, t_x = 2013) = \\ &= \int\int f(w|d, x, t_w = 2013) dF(d|x, t_{d|x} = 2013) dF(x|t_x = 2013) \end{aligned} \tag{3.16}$$

Under the assumption that the conditional density $f(w|d, x, t_w)$ does not depend on the temporary contract status, the density that would have prevailed in 2013 if temporary contract, but none of the other attributes, had remained at its 2007 level can be written as a reweighted version of the 2013 density:

$$\begin{aligned} &f(w; t_w = 2013, t_{d|x} = 2007, t_x = 2013) \\ &= \int\int f(w|d, x, t_w = 2013) dF(d|x, t_{d|x} = 2007) dF(x|t_x = 2013) \\ &= \int\int f(w|d, x, t_w = 2013) \psi_{d|x}(d, x) dF(d|x, t_{d|x} = 2013) dF(x|t_x = 2013) \end{aligned} \tag{3.17}$$

where $\psi_{d|x}(d,x)$ is the reweighting function defined as

$$\begin{aligned}\psi_{d|x}(d,x) &= \frac{dF(d|x,t_{d|x}=2007)}{dF(d|x,t_{d|x}=2013} \\ &= d \cdot \frac{Pr(d=1|x,t_{d|x}=2007)}{Pr(d=1|x,t_{d|x}=2013)} \\ &+ [1-d] \cdot \frac{Pr(d=0|x,t_{d|x}=2007)}{Pr(d=0|x,t_{d|x}=2013)}\end{aligned} \tag{3.18}$$

An estimate of the reweighting function $\psi_{d|x}(d,x)$ can be obtained by estimating the conditional probability $Pr(d=1|x,t_{d|x})$ for $t_{d|x}=2007$ and $t_{d|x}=2013$ using a Probit model.

To account also for the role of attributes in the changes of the wage distributions in the two years, we consider the density of wages that would have prevailed in 2013 if the distribution of both d and x had remained as in 2007

$$\begin{aligned}&f(w;t_w=2013,t_{d|x}=2007,t_x=2007) \\ &= \int\int f(w|d,x,t_w=2013)dF(d|x,t_{d|x}=2007)dF(x|t_x=2007) \\ &= \int\int f(w|d,x,t_w=2013)\psi_{d|x}(d,x)dF(d|x,t_{d|x}=2013)\psi_x(x) \\ &\quad \times dF(x|t_x=2013)\end{aligned} \tag{3.19}$$

where

$$\begin{aligned}\psi_x(x) &= \frac{dF(x|t_x=2007)}{dF(x|t_x=2013)} \\ &= \frac{Pr(t_x=2007|x)}{Pr(t_x=2013|x)} \cdot \frac{Pr(t_x=2013)}{Pr(t_x=2007)}\end{aligned} \tag{3.20}$$

for Bayes' rule. Again these conditional probabilities can be estimated with a Probit model. We can then apply the following sequential decomposition:

$$\begin{aligned}&f_{2013}(w) - f_{2007}(w) = \\ &= f(w;t_w=13,t_{d|x}=13,t_x=13) - f(w;t_w=13,t_{d|x}=07,t_x=13) + \\ &+ f(w;t_w=13,t_{d|x}=07,t_x=13) - f(w;t_w=13,t_{d|x}=07,t_x=07) + \\ &+ f(w;t_w=13,t_{d|x}=07,t_x=07) - f(w;t_w=07,t_{d|x}=07,t_x=07)\end{aligned} \tag{3.21}$$

where the second line indicates the "effect" of changes in the level of temporary contracts, the third line the "effect" of changes in the distribution of all other attributes, and the last line the residual factors, i.e. the change in the structure of labour market after the economic crisis.

3.2.3 Distribution of Summary Statistics

Sometimes it is interesting to observe changes not only on the entire distribution of an outcome but also for general distributional measures that can be significant in summing up the results. The assumptions that has been discussed here are valid, as proved by Fortin et al. (2011), also for some statistics of the distribution defined as $\nu(F_{Y_d|D_r})$ where $\nu : \mathscr{F}_\nu \to \mathbb{R}$ is a real-valued functional and where $\mathscr{F}_\nu$ is a class of distribution functions such that $F_{Y_d|D_r} \in \mathscr{F}_\nu$ if $|\nu(F_{Y_d|D_r})| < \infty, d, r = 0, 1$ (Fortin et al., 2011). DiNardo et al. (1996) and Chernozhukov et al. (2013) also include in their estimation of counterfactual distributions, the computation of some of these statistics. In our work we will consider two measures calculated from the counterfactual distribution f^*: the quantiles of the distribution w_τ defined as

$$w_\tau := \int_0^{w_\tau} f^*(w)dw = \tau \tag{3.22}$$

and the Gini coefficient

$$G_{F^*} = 1 - 2\int_w L(w, F_W^*)dw \tag{3.23}$$

calculated from the Lorenz curve as the ratios of partial means to overall means:

$$L(w, F_W^*) = \frac{\int_w 1(\tilde{w} < w)dF^*(\tilde{w})}{\int_w \tilde{w}dF^*(\tilde{w})} \tag{3.24}$$

In the following Chapter we will presents the results of the empirical analysis together with the description of the data and the sample. The decomposition results and some significant conclusions will be provided.

Chapter 4

Empirical Analysis

4.1 The EU-SILC Data

The European Union-Survey on Income and Living Conditions (EU-SILC) is the EU reference source for micro data on income, poverty, social exclusion and living conditions both at household and individual level. The dataset includes internationally and cross-temporary comparable variables for all EU Member States and some other counties. It was launched in 2004 in 13 Member States[1]. From 2005 onwards the data are available for all EU25 Member States plus Island and Norway[2].

4.1.1 Reference population and sample design

The reference population of EU-SILC is defined as "all private households and all persons aged 16 and over within the household residing in the territory of the Member States at the time of data collection. Persons living in collective households and in institutions are generally excluded from the target population. For practical reasons, small parts of the national territory may also not be covered in the survey (e.g. the French Overseas Departments and territories; Scotland north of the Caledonian Canal and the Scilly Islands)"(Eurostat, 2018). EU-SILC data are collected by National Statistical Institutes, for Italy ISTAT is in charge, and could come from different sources. The information are stored in

[1]Belgium, Denmark, Estonia, Greece, Spain, France, Ireland, Italy, Luxembourg, Austria, Portugal, Finland and Sweden plus in Norway and IS

[2]Turkey, Romania, Bulgaria and Czech Republic have launched EU-SILC in 2006.

four different datasets: the Household register, the Household data file, the Personal register and the Personal data file with the possibility of matching them together.

EU-SILC is a complex survey involving different sampling designs in different countries and the sample design for Italy could be assimilated to a two stage stratified type[3]. Unfortunately, important sample design variables are missing in the EU-SILC User Database (UDB) and previous studies have shown that neglecting the sample design can lead to an underestimation of standard errors (Goedemé, 2013). Goedemé (2010) analyses extensively the quality of the standard errors. He shows that for variables calculated at household level (like income and poverty measures) accounting for clustering within households is of paramount importance but taking as much as possible account of the entire sample design generally leads to more accurate estimates, even if sample design variables are partially lacking. Even though this analysis focuses on variables collected at individual level we still take account for the sample design.

4.1.2 Variables of interest

Since the Great Recession began between 2008 and 2009, we choose 2007 cross-sectional wave to represent the status of the labour market before the crisis. As the reference year for the post crises situation we choose the 2013 cross-sectional wave , with a seven year gap in between, since in Europe the effects were more enduring than in the U.S (Commission, 2013a). With this selection we might be able to capture the changes brought along by this turning-point event. We decided to focus on workers wages, in particular on gross monthly earnings for employees. It corresponds to the monthly amount in the main job for employees before tax and social insurance contributions deduction. It includes salary, tips and commission but excludes income from investments-assets, savings, stocks and shares. If a person receives, as a part of a salary, supplementary payments (13th or 14th month payments), or payments such as holiday pay, profit share, bonuses, these payments are taken into account on a monthly basis. Only monetary earnings are taken into

[3]The first stage units (or primary sampling units PSU) are the municipalities, the second stage units (SSU) are the households. The PSU are stratified according to their size in terms of number of residents. Stratification is carried out inside each administrative region. Four municipalities are selected in each stratum. Municipalities are clusters of households, households are clusters of individuals.

account (Eurostat, 2018). Using available information on how many months are spent in paid work and how may hours are worked per week, a new wage-per-hour variable has been calculated and logarithmically transformed to be used as the outcome variable of interest. Moreover wages have been adjusted using ISTAT FOI index, i.e. the consumer price index for worker-headed households, to make comparable the 2007 and 2013 surveys.

As covariates I make use of the following individual variables: gender, age level, education level, skills, experience, full-time or part-time status, a managerial position dummy, the dimension of the local unit, the job sector, being an immigrant, marital status, number of children and five regional dummies. Education level was build upon the International Standard Classification of Education (ISCED) and recoded to fit a three-level variable. The first level includes people with a a degree up to a lower secondary education, the second level includes upper secondary and post-secondary (but non tertiary) degrees, and the third level encompass individual that graduated from a first or second stage of tertiary education (UNESCO, 2011). As defined by International Labour Organization (ILO), skill is the ability to carry out tasks and duties of a given job. Moreover skill level is measured operationally by considering the nature of the work performed, the level of formal education completed and the informal on-the-job-training (ILO, 2011). The International Standard Classification of Occupations (ex ISCO-88, now ISCO-08[4]) defines four levels of skills that remained comparable after the new coding. They go from elementary occupations (level 1) to highly professional positions (level 4) and are used as a variable for skill level. Experience is defined upon years of work experience, age is divided in five classes and the marital status is a three-level variable for people who have never been married, people who are currently married or living with a partner, and people who used to be married (separated, divorced, widowed). The job sector is defined according to the Statistical classification of economic activities in the European Community (NACE) in a way that the 2007 and 2013 are comparable.

I excluded from the analysis individuals aged under 15 and individuals aged over 65. I also excluded people in the armed forces. The sample is thus composed by working employed individuals and contains 14365 observations in 2007 and 11569 in 2013. The selection of 2007 and 2013 as the reference years allows to analyse the social and economic scenarios along the global crisis.

[4]from 2011

4.2 Descriptive statistic of sample

Here we present some descriptive statistics of the sample, divided by type of contract and years[5]. Starting with Tab. 4.1, the composition of the sample, we can see that the share of women shows a rise between 2007 and 2013, for both types of contracts, in line with the fact that the share of unemployed people growth especially for men (see Tab.2.1). Regarding age classes it is evident that the share of young workers (first and second cohort) have a drop in respect to older groups, reflecting again the differences shown in Tab.2.1 for unemployment and inactive shares. It is worth noting that within permanent workers, the youngest cohort is less than 7% in both years, while within the temporary group the share is more than 20%. Low educated people also suffered a drop in the sample between the two years while the presence of highly educated ones rises. This trend is reproduced inside the two groups of workers as well. Talking about skills, in 2013 the share of workers belonging to the lowest level increases the share in the temporary contracts' group of 3 percentage points while it remains stable in the other one. In general, for 2013, the lower and the higher skill groups see an increase in their share, while the medium-high skilled group suffered a 5% drop. This might be a first indication of the presence of job-polarisation type of change for the structure of the market. While the general share of Italian and non-Italian workers remains stable across years, a shift of proportions inside the temporary group can be noticed, with a rise in the share of non citizen workers. Finally an increase of 3% is present also for the share of workers under a part-time schedule, and it regards both temporary and permanent contracts.

If we compare means of the log of hourly wages in Tab.4.2 it is possible to notice that in both years the mean for permanent workers in all the sub-groups is higher than their counterparts with a temporary arrangement. If we compare each group of workers within the two years it possible to notice that both suffered a decrease in the mean value of the log wages but the bigger drop occurred for the temporary group, in particular for young, high educated, low skilled and full time sub-groups.

When we observe Gini coefficients in Tab. 4.3 we can see that the inequality is generally higher for the temporary workers in both years and for every sub-group. Within the temporary workers, the time comparison shows a bigger increase especially for males, young, low educated and low skilled workers.

[5]Our data sources were EUSILC UDB 2013 - Version of January 2016 and EUSILC UDB - Version of August 2011

Table 4.1: Percentage of Personal Characteristics

	Permanent Contract		Temporary Contract		All Population	
Gender	2007	2013	2007	2013	2007	2013
Female	39,8%	45,1%	50,4%	48,5%	41,5%	45,6%
Male	60,2%	54,9%	49,6%	51,5%	58,5%	54,4%
Age class						
15 - 25	6,8%	4,1%	24,0%	20,5%	9,6%	6,4%
25 - 35	27,2%	20,5%	35,1%	33,1%	28,5%	22,2%
35 - 45	32,9%	32,7%	24,6%	25,4%	31,5%	31,7%
45 - 55	26,3%	31,4%	13,2%	15,0%	24,2%	29,1%
55 - 65	6,9%	11,4%	3,1%	5,9%	6,3%	10,6%
Education						
Low	6,1%	2,7%	9,5%	6,0%	6,7%	3,1%
Medium	76,4%	75,9%	74,6%	75,4%	76,1%	75,9%
High	17,5%	21,4%	15,9%	18,6%	17,2%	21,0%
Skills						
Level 1	9,5%	9,5%	17,0%	20,5%	10,7%	11,0%
Level 2	53,3%	54,4%	56,6%	57,0%	53,8%	54,7%
Level 3	24,5%	18,3%	18,2%	9,5%	23,5%	17,1%
Level 4	12,7%	17,9%	8,3%	13,1%	12,0%	17,2%
Citizen						
No	93,0%	93,1%	86,5%	88,9%	92,4%	92,5%
Yes	6,4%	6,9%	13,5%	11,1%	7,6%	7,5%
Schedule						
Part- Time	10,1%	14,0%	24,8%	26,5%	12,5%	15,7%
Full - Time	89,9%	86,1%	75,2%	73,5%	87,5%	84,3%
Marital Status						
Never Married	30,4%	29,6%	50,3%	53,4%	33,7%	32,8%
Married	61,4%	61,1%	44,1%	40,2%	58,6%	58,2%
Was Married	8,1%	9,33%	5,7%	6,4%	7,7%	8,9%

Table 4.2: Mean of Log of Hourly Wages by Sub-Groups

Mean of Log of Hourly Wages	Permanent Contract		Temporary Contract	
	2007	2013	2007	2013
Gender				
Female	2,41	2,36	2,16	2,05
Male	2,47	2,46	2,15	2,08
Age class				
15 - 25	2,08	2,10	2,00	1,95
25 - 35	2,34	2,30	2,20	2,11
35 - 45	2,48	2,43	2,23	2,10
45 - 55	2,56	2,48	2,16	2,09
55 - 65	2,65	2,51	2,23	2,05
Education				
Low	2,26	2,12	2,02	1,92
Medium	2,38	2,36	2,11	2,04
High	2,80	2,65	2,46	2,24
Skills				
Level 1	2,18	2,14	2,00	1,88
Level 2	2,33	2,32	2,10	2,04
Level 3	2,56	2,54	2,28	2,25
Level 4	2,92	2,72	2,55	2,32
Citizen				
No	2,46	2,43	2,17	2,08
Yes	2,20	2,14	2,01	1,94
Schedule				
Part- Time	2,30	2,29	2,12	2,06
Full - Time	2,47	2,43	2,18	2,07
Marital Status				
Never Married	2,32	2,30	2,09	2,06
Married	2,51	2,47	2,23	2,08
Was Married	2,49	2,41	2,15	1,99

Table 4.3: Gini Coefficient for of Log of Hourly Wages for SUb-Groups

Gini Coeff. (Log of Hourly Wages)	Permanent Contract		Temporary Contract	
	2007	2013	2007	2013
Gender				
Female	0,097	0,095	0,119	0,109
Male	0,088	0,088	0,103	0,116
Age class				
15 - 25	0,091	0,102	0,096	0,103
25 - 35	0,075	0,081	0,114	0,109
35 - 45	0,086	0,084	0,105	0,120
45 - 55	0,091	0,093	0,117	0,102
55 - 65	0,105	0,102	0,113	0,135
Education				
Low	0,08	0,11	0,10	0,11
Medium	0,08	0,09	0,10	0,11
High	0,09	0,09	0,12	0,11
Skills				
Level 1	0,09	0,10	0,11	0,12
Level 2	0,08	0,08	0,09	0,10
Level 3	0,08	0,07	0,11	0,12
Level 4	0,09	0,08	0,13	0,11
Citizen				
No	0,09	0,09	0,11	0,11
Yes	0,08	0,09	0,10	0,10
Schedule				
Part- Time	0,10	0,10	0,11	0,12
Full - Time	0,09	0,09	0,11	0,11
Marital Status				
Never Married	0,09	0,10	0,11	0,11
Married	0,09	0,09	0,11	0,11
Was Married	0,10	0,10	0,11	0,12

4.3 The Discrimination Effect of Temporary Contracts

In the following paragraphs the empirical results of the semi-parametric estimation of the counterfactuals distributions and the subsequent decompositions are shown. We start presenting results for 2013 only, describing what kind of wage discrimination temporary workers are suffering, then we will move to the comparison over time with the aim to characterize what structural change in the labour market has occurred in Italy during the years 2007-2013 in the aftermath of the Great Recession and to understand and their potential relationships with wage inequality.

The decomposition results for the wage distributions of temporary and permanent contracts in 2013 are plotted in Figure 4.1. On the left side the real wage distribution for individuals with a temporary contract is represented with a solid line, superimposed on the counterfactual distribution defined in Equation 3.7 and identified by a dotted line. This represents in a visual way the effect of changes in the distribution of individual characteristics in the two groups, also defined earlier as composition effect. On the right side the dotted line of the counterfactual distribution is plotted against the solid line that represent the distribution of wages for individuals with a permanent contract. This side of the graph shows the change in wages due only to the type of contract, visually representing the wage penalty. Indeed the difference between these two distribution is determined only by the type of contract since other job-related characteristics are considered equal thanks to the proper reweighting function.

To give some numerical benchmark for the changes represented in Figure 4.1, we computed the quantiles of both the real distributions and of the counterfactual as explained in sub-paragraph 3.2.3 so that the decomposition of Eq. 3.7 could be applied to these quantities. The results are presented in Table 4.4 in which the total change indicate the difference between the two real distributions (temporary contracts wages minus permanent) at given quantiles, and the last two columns indicate the share of variation imputable to changes in the covariates or in the unexplained part, the wage penalty. The total changes are negative all along the distribution, meaning that at each quantile the distribution of wages for temporary contracts is lower and both the attributes and the residual part contribute to lower the distribution. This means that while there might be a difference in salaries between the two groups due to differences in personal endowments, still a big part of the gap is imputable to a contractual discrimination. The fact that personal characteristics are more relevant at the highest part of the wage distribution may be a indication that for high-paid jobs temporary contracts may work as a sort of selection method in which high skilled workers face interim working agreements to qualify for better positions in a second moment (Bosio, 2013). On the other hand, what has been concerning the most is the fact that in 2013 the percentage of variation due to the wage penalty is much stronger in the lower part of the distribution. This first important result is consistent with the literature that identifies the burdens of reforms that improve the flexibilisation of the labour market only at the margins on workers at the bottom of the wage distribution. The creation of a parallel system of working arrangements in which protections and rights are unevenly spread across them seems to produce a discriminatory effect concentrated among workers with low skill and low education levels. The problem with the sticky floor effect for this kind of penalty is that a form segregation of workers is maintained in the lower part of the wage distribution where low skilled workers (because of education, or because their age) risk to face systematically lower wages, lesser trainings and more instability (Comi & Grasseni (2012), Bosio (2013), Santangelo (2011)). If we repeat the same analysis separately for 2007 (4.4) it is interesting to notice that before the economic crisis, close to the time when this kind of contracts were introduced[6], the wage penalty was still present but was more spread along the entire distribution.

4.3.1 Wage Penalty for sub-groups of workers

Still focusing on 2013, we now consider subgroups of workers population to inquiry if the wage penalty behaves differently for different groups of people and results are presented in Table 4.5, Table 4.6 and Table 4.7. Graphs of the wage decomposition for sub-groups are presented in Appendix (from Figure 4 to Figure 11). Taking a look at the Table 4.5 and 4.6 it is possible to notice that, since the total change is always negative, positive shares of change means that it is concurring to extend the change while a negative sign of the share means it is reducing the difference. The wage penalty for men seems to reproduce the general effect with the share of unexplained difference bigger in the lower part

[6]The most important reforms in Italy were legislated between 2001 and 2003 and put in practice starting from 2005 (Bosio (2013), Bolelli (2017))

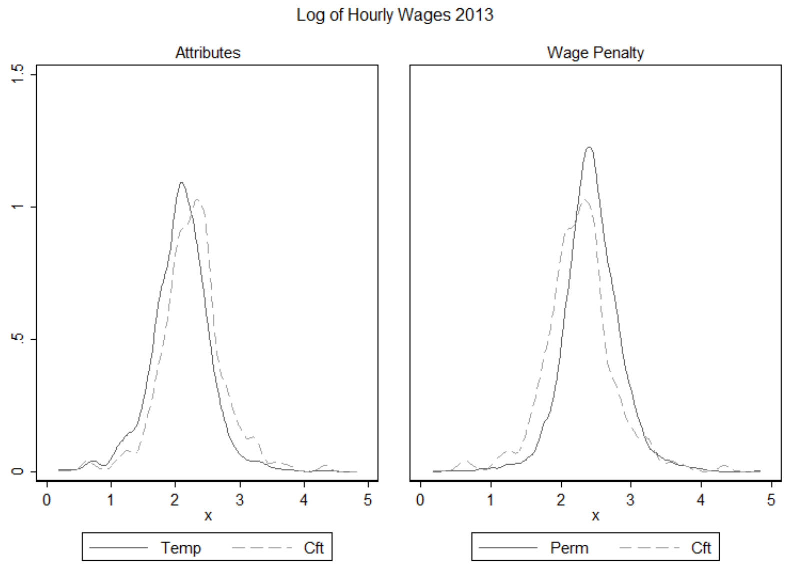

Figure 4.1: Decomposition of Wage Distribution 2013

Table 4.4: Decomposition of Quantiles on Log of Hourly Wages

2013	Total Change	Attributes*	Unexplained
10th Quantile	-0,405	46%	54%
25th Quantile	-0,351	50%	50%
50th Quantile	0,328	60%	40%
75th Quantile	-0,328	53%	47%
90th Quantile	-0,346	77%	23%
2007	**Total Change**	**Attributes**	**Unexplained**
10th Quantile	-0,318	70%	30%
25th Quantile	-0,294	63%	37%
50th Quantile	-0,268	53%	47%
75th Quantile	-0,278	66%	34%
90th Quantile	-0,460	70%	30%

*Percentages are calculated dividing each component by the the total variation.

of the distribution. Women on the other hand show a slightly different pattern with the wage penalty more "equally" spread among the distribution. Results for the two middle level of skill are not so clear even though they seem to suggest again a spread of the wage penalty among the distribution. A different picture is drawn for the lower and higher levels of skill for which the wage penalty is stronger at the bottom of the distribution up to the median. Regarding age classes, the changes in the youngest cohort is almost entirely explained by the wage gap but this might be not so surprising since the group include people who just entered the job market and they might not differ a lot in individual attributes. For young workers (from 25 to 35 years old) the wage penalty is more evident in the middle of the distribution while for the following cohort (from 35 to 45 years old) the sticky floor effect is present again. For the last cohort results are not so clear but this may be due to the fact that the sample size for this group of workers might be small due to early retirements. Finally the total change in the Gini coefficient is positive for all the subgroups meaning that inequality in the distribution is bigger for individuals with temporary contracts. The wage penalty increases the Gini coefficient for all the sub-groups while, exception for the two middle skill levels, the attributes tend to lower the difference between the coefficients of the two groups.

Since Italy is characterized by profound regional differences, we repeated the analysis considering the three typical main geographical areas: the North[7], the Center[8] and the South together with the islands [9]. It is worth noting that the wage penalty presents some peculiar characteristic for each group. In the northern region the penalty is higher at the bottom of the distribution and decreases along the rest of it but it never exceed the 55% of the difference between the two wages. The central regions follow the same pattern even though the wage penalty at the bottom of the distribution is higher then the northern regions. On the other hand in the South of Italy the situation that emerges from the analysis is quite the opposite. The wage penalty grows from the bottom to the top of the distribution going from explaining the 55% of the difference up to the 82% at the ninth quartile. It is possible to say then that the Southern part of Italy suffers the most regarding the wage penalty associated with this type of more flexible working agreement. Moreover, while the northern and the central regions of Italy are

[7]Val d'Aosta, Piemonte, Liguria, Lombardia, Emilia-Romagna, Veneto, Trentino-Alto Adige e Friuli Venezia-Giulia.

[8]Toscana, Umbria, Marche e Lazio

[9]Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia e Sardegna

characterised by the "sticky floor" effect, the South instead suffers of a "glass ceiling" barrier[10]. This effect reproduces a wider gap at the top of the distribution, implying that the disadvantaged group of temporary workers is paid significantly less than their permanent counterpart in the high-paid jobs (Bosio, 2013). Anyway in both cases we assist a polarisation of the wage distribution. Also the Gini coefficient behaves in the same way for North and Centre, presenting higher values for the temporary groups and with the attributes that tend to equalize the index between the two groups. In the southern region though, while the Gini coefficient is still higher for the temporary group, both the attributes and the wage penalty concur in increasing the inequality between the groups meaning that there are differences in characteristics between the workers of the two groups.

4.4 Decomposing Changes in Wage Distribution Across Time

We now consider the two years 2007 and 2013. We apply a detailed decomposition illustrated in Eq. 3.21 to disentangle the effect of changes in the level of temporary contracts, changes in covariate distribution and changes in the wage structure due to the economic crisis occurred between those years. Results are plotted in Figure 4.2. The weighted kernel estimate of the counterfactual densities are plotted in dash lines against both the two real distribution of wages of 2007 and 2013. Each graph represent a line in the Eq. 3.21: the first on the top left is the 2013 wage distribution against the weighted kernel estimate of the counterfactual density which represents the effect of changes in the distribution of temporary contracts rate. The second one, on the top right, represents the two estimated counterfactual distributions: the effect of changes in the distribution of temporary contracts and of the other job-related covariates. Finally, the third graph, on the bottom left, is the 2007 wage distribution against the counterfactual for changes in all the covariates which represents the residual unexplained variance, our main interest. It is possible to notice from Table 4.8 that the overall change between 2013 and 2007 is always negative showing, if not a decrease, for sure not an increase in the salaries in line with all previ-

[10]Introduced in the 1980s, the glass ceiling is a metaphor for the invisible barriers that block minorities (usually it used applied on wage differences for women) from advancing up the ladder to management positions (Johns, 2013)

Table 4.5: Decomposition of Quantiles on Log of Hourly Wages 2013 for Sub-Groups of Population (a)

Males	Total Change	Attributes	Unexplained
Gini	0,027	-17%	117%
10th Quantile	-0,470	47%	53%
25th Quantile	-0,400	59%	41%
50th Quantile	-0,357	75%	25%
75th Quantile	-0,329	68%	32%
90th Quantile	-0,387	130%	-30%
Females	Total Change	Attributes	Unexplained
Gini	0,014	-60%	160%
10th Quantile	-0,318	37%	63%
25th Quantile	-0,300	39%	61%
50th Quantile	-0,288	45%	55%
75th Quantile	-0,338	57%	43%
90th Quantile	-0,318	86%	14%
North	Total Change	Attributes	Unexplained
Gini	0,018	-13%	113%
10th Quantile	-0,344	48%	52%
25th Quantile	-0,295	55%	45%
Median	-0,290	71%	29%
75th Quantile	-0,295	70%	30%
90th Quantile	-0,272	82%	18%
Centre	Total Change	Attributes	Unexplained
Gini	0,013	-35%	135%
10th Quantile	-0,262	34%	66%
25th Quantile	-0,248	50%	50%
Median	-0,280	73%	27%
75th Quantile	-0,334	55%	45%
90th Quantile	-0,570	89%	11%
South	Total Change	Attributes	Unexplained
Gini	0,017	62%	38%
10th Quantile	-0,357	45%	55%
25th Quantile	-0,352	48%	52%
Median	-0,377	28%	72%
75th Quantile	-0,352	34%	66%
90th Quantile	-0,350	18%	82%

Table 4.6: Decomposition of Quantiles on Log of Hourly Wages 2013 for Sub-Groups of Population (b)

15 - 25	Total Change	Attributes	Unexplained
Gini	0,001	440%	-340%
10th Quantile	-0,041	0%	100%
25th Quantile	-0,104	0%	100%
50th Quantile	-0,172	-12%	112%
75th Quantile	-0,178	-8%	108%
90th Quantile	-0,182	0%	100%
25-35	Total Change	Attributes	Unexplained
Gini	0,028	16%	84%
10th Quantile	-0,277	59%	41%
25th Quantile	-0,236	35%	65%
50th Quantile	-0,182	31%	69%
75th Quantile	-0,167	53%	47%
90th Quantile	-0,153	67%	33%
35-45	Total Change	Attributes	Unexplained
Gini	0,036	53%	47%
10th Quantile	-0,486	50%	50%
25th Quantile	-0,403	62%	38%
50th Quantile	-0,319	72%	28%
75th Quantile	-0,226	62%	38%
90th Quantile	-0,227	70%	30%
45-55	Total Change	Attributes	Unexplained
Gini	0,010	-140%	240%
10th Quantile	-0,422	71%	29%
25th Quantile	-0,372	44%	56%
50th Quantile	-0,325	62%	38%
75th Quantile	-0,405	98%	2%
90th Quantile	-0,446	77%	23%
55-65	Total Change	Attributes	Unexplained
Gini	0,033	27%	73%
10th Quantile	-0,478	115%	-15%
25th Quantile	-0,479	85%	15%
50th Quantile	-0,420	100%	0%
75th Quantile	-0,424	140%	-40%
90th Quantile	-0,335	261%	-161%

Table 4.7: Decomposition of Quantiles on Log of Hourly Wages 2013 for Sub-Groups of Population (c)

Skill Level 1	Total Change	Attributes	Unexplained
Gini	0,024	-47%	147%
10th Quantile	-0,350	24%	76%
25th Quantile	-0,571	20%	80%
50th Quantile	-0,223	36%	64%
75th Quantile	-0,267	63%	37%
90th Quantile	-0,173	123%	-23%
Skill Level 2	Total Change	Attributes	Unexplained
Gini	0,016	34%	66%
10th Quantile	-0,316	42%	58%
25th Quantile	-0,295	43%	57%
50th Quantile	-0,251	47%	53%
75th Quantile	-0,250	55%	45%
90th Quantile	-0,262	36%	64%
Skill Level 3	Total Change	Attributes	Unexplained
Gini	0,042	43%	57%
10th Quantile	-0,399	74%	26%
25th Quantile	-0,370	66%	34%
50th Quantile	-0,341	19%	81%
75th Quantile	-0,339	84%	16%
90th Quantile	-0,112	135%	-35%
Skill Level 4	Total Change	Attributes	Unexplained
Gini	0,029	-157%	257%
10th Quantile	-0,479	-14%	114%
25th Quantile	-0,405	-8%	108%
50th Quantile	-0,342	-12%	112%
75th Quantile	-0,348	63%	37%
90th Quantile	-0,376	41%	59%

ous findings. Whilst the share of temporary contracts have almost a residual factor, the covariates change seems to have a positive effect. According to DiNardo et al. (1996) this might be due to the increase in the average number of years of schooling which would be supported by the descriptive statistics of the sample in Tab 4.4. This expanding effect is almost completely annulled by the effect of change in the residual part, or as we call it the wage structure. To us this is a first row measurement of the impact of change in the labour market structure due to the economic crisis, with all its complex dynamics. However a pure economist might say that residual part is only a ”measure of our non-knowledge” so further discussion is required to give a more specific interpretation of what ”economic crisis” means and may imply in terms of wage dynamics. The results show that the way jobs are rewarded had followed a downward path and this residual factor explains the majority of the ”stikness” of salaries (Arpaia & Curci, 2010), in line with what was discussed in Castellano et al. (2017). Martins et al. (2012) pointed out that recent literature has found that real wages tend to be pro-cyclical and that the cyclical elasticity of real wages is similar to that of employment. So it is not unexpected to find a negative wage growth during the recession. Indeed Schaefer & Singleton (2017) show that UK firms were able to respond to the Great Recession with substantial real wage cuts and by recruiting more part-time workers. Elsby et al. (2016) found the same pattern for UK and USA but they found difficult to explain their results only on the basis of a downward nominal wage rigidity hypothesis, and they inquire for more research on the topic. Arpaia & Curci (2010) suggest that while unemployment put a decreasing pressure on wages, the decline in productivity growth caused by the recession may have increased unit labour costs. They also suggest that the decline in wages has been led by the fall in the variable component which exceeded the relative invariance of negotiated wages. This type of response may have created competitive pressures at the early stage of the recovery if negotiated wages did not incorporate the impact of the recession. They also found heterogeneous impact of the crisis on different socio-economic groups and to asses this aspect in our empirical case we will later proceed in comparing results for subgroups. To conclude this reflection on what this residual effect means, it is worth introducing the concept of functional income distribution defined as ”the distribution of income among the owners of the various factors of production. Wages accrue to labour, rent to landlords, and interest, dividends, and retained profits of companies to capital” (John Black & Myles, 2009). Indeed a new brunch of literature have been focusing recently on the fact that functional income distribution underwent drastic changes in the past decades, along a broader trend of increasing inequality, from which Stockhammer (2013) and Francese & Mulas-Granados (2015) are just two examples[11]. Stockhammer (2013) in particular inquiries the relative impact of financialisation, globalisation, welfare state shortfall and technological change on functional income distribution. He suggests that financialisation has been the main cause of the decline in the wage share with globalisation, technological change and the decline in welfare state funding having also had substantial negative effects. Moreover Stockhammer (2013) explains that financialisation has two important effects on bargaining position of labour: it gave mobility to firms in their investments and it has empowered shareholders relative to workers. This lead to represent income distribution as the result of a bargaining process between firms and labour, typically represented by labour unions. A lower bargaining power of workers could then lead to a decrease in wages and, if labour demand is inelastic, to a decrease in the wage share.

Table 4.8: Decomposition of Quantiles on Log of Hourly Wages 2013 - 2007

All Population	Total Change	Temporary Contract	Attributes	Unexplained
10th Quantile	-0,048	-17%	-116%	233%
25th Quantile	-0,030	-4%	-39%	143%
50th Quantile	-0,007	-29%	-80%	209%
75th Quantile	-0,023	-9%	-147%	257%
90th Quantile	-0,080	0%	-43%	143%

Comparing results for men and women separately, it is possible to see that for men results are less clearer while for women the impact of the economic crisis on wages distribution has been important all over the distribution. Again changes in covariates seem to suggest an improvement in the attributes but this is not sufficient to overcome the negative effect of the change in the wage structure. However in both groups changes in the share of temporary contracts have a residual factor. This results is in line again with the findings of Elsby et al. (2016) which found men's real wages less affected in the Recession while for

[11]Other examples are Lazonick & O'Sullivan (2000), Duménil & Lévy (2001), Gérard & Dominique (2004) Rossman (2009), Hein & Schoder (2011), Onaran et al. (2011) and Argitis & Pitelis (2001).

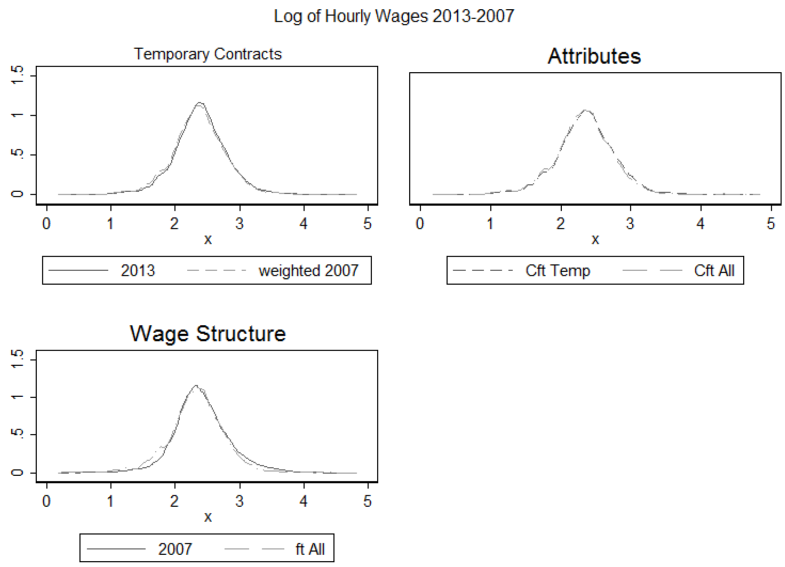

Figure 4.2: Decomposition of Wage Distribution 2013 - 2007

women the impact was particularly strong. We present now the results for low and high skill levels. Looking at Tab. 4.10 (Figures are in Appendix) it is possible to notice that also in this case the change in the wage structure has the strongest impact in preventing the 2013 wages to grow. However for lower skills this negative impact seems to be stronger not only in the lower tail but for the whole distribution. High skill distribution seems though to be less affected and only up until the median. This might be a suggestion that the change in the structure of the labour market is in fact polarising in which especially low skilled groups are affected. To conclude we would like to stress that the OECD Employment Outlook 2018 OECD (2018b) recently focused the attention that, while employment rates have finally recovered and surpassed the pre-crisis levels, wage growth is still very slow and not equal in the workforce. Even though macro-economists are still debating over this topic, in the report they suggest the one of the reasons lies with the change in the skill demand. As they stated jobs destroyed during the crisis are not the same as those created in the recovery and high skilled jobs has been recently the main beneficiaries of the wage growth (and at the same time less affected by the negative changes in the structure of the market.) Finally we present the analysis for each macro-region, namely the North and the South plus Island, as we did in the previous paragraph. We now refer to Tab 4.11 (figures are in Appendix) where it is worth nothing that the effect of the crisis on wages is much more visible in the southern regions. This indicates that in regions already considered struggling from an economical point of view, also the shrinking of wages occurred in a greater way. As a control for the results

Table 4.9: Decomposition of Quantiles on Log of Hourly Wages 2013 - 2007 for Males and Females

Males	Total Change	Temporary Contracts	Attributes	Unexplained
10th Quantile	-0,043	0%	-132%	232%
25th Quantile	2,992	100%	1%	-1%
50th Quantile	0,006	-24%	574%	-450%
75th Quantile	-0,005	80%	-683%	703%
90th Quantile	-0,032	11%	-162%	252%
Females	Total Change	Temporary Contracts	Attributes	Unexplained
10th Quantile	-0,117	0%	0%	100%
25th Quantile	-0,035	-24%	-20%	144%
50th Quantile	-0,014	-27%	-113%	239%
75th Quantile	-0,041	-9%	-55%	164%
90th Quantile	-0,114	0%	-34%	134%

presented so far, we repeated the analysis including a year in between, namely the 2010, to better analyse the temporal impact of changes due to the Great Recession that may have been included in the residual part. Fore sake of brevity we present results only for the aggregate part. First we present the results for the decomposition of wage differentials between 2007 and 2010, then the decomposition between 2010 and 2013. While the total change is positive for the period 2007-2010, it becomes negative in the period 2010-2013. It is possible to see how the dynamics described before are still valid, what changes is basically the magnitude of the effect so it possible that the negative effects on wages discussed before revealed themselves in the second part of the period considered.

4.5 Conclusions

To draw some conclusions it is possible to say that the decrease in real wages caused by the Great Recession is in line with previous finding

Table 4.10: Decomposition of Quantiles on Log of Hourly Wages 2013 - 2007 For Skill Level 1 and 4

Skill Level 1	Total Change	Temporary Contracts	Attributes	Unexplained
10th Quantile	-0,117	-3%	193%	-90%
25th Quantile	-0,094	-43%	254%	-111%
50th Quantile	-0,03	-12%	426%	-314%
75th Quantile	-0,03	-25%	336%	-211%
95th Quantile	-0,029	-102%	276%	-74%
Skill Level 4	Total Change	Temporary Contracts	Attributes	Unexplained
10th Quantile	-0,048	-78%	505%	-327%
25th Quantile	-0,079	-36%	266%	-129%
50th Quantile	-0,216	-2%	116%	-15%
75th Quantile	-0,314	0%	73%	27%
90th Quantile	-0,345	-4%	85%	19%

Table 4.11: Decomposition of Quantiles on Log of Hourly Wages 2013 - 2007 By Regions

North	Total Change	Temporary Contracts	Attributes	Unexplained
10th Quantile	-0,021	-17%	-158%	275%
25th Quantile	-0,012	0%	0%	100%
50th Quantile	0,014	0%	174%	-74%
75th Quantile	-0,010	0%	-155%	255%
90th Quantile	-0,041	6%	-73%	167%
South and Islands	Total Change	Temporary Contracts	Attributes	Unexplained
10th Quantile	-0,074	0%	-17%	117%
25th Quantile	-0,080	0%	-19%	119%
50th Quantile	0,030	0%	0%	100%
75th Quantile	-0,043	-27%	-32%	159%
90th Quantile	-0,175	0%	-20%	120%

Table 4.12: Decomposition of Quantiles on Log of Hourly Wages 2013-2010-2007

2007-2010	Total Change	Temporary Contracts	Attributes	Unexplained
10th Quantile	0,032	22%	10%	69%
25th Quantile	0,026	0%	0%	100%
50th Quantile	0,041	7%	3%	90%
75th Quantile	0,027	0%	8%	92%
90th Quantile	-0,010	0%	0%	100%
2010-2013	Total Change	Temporary Contracts	Attributes	Unexplained
10th Quantile	-0,080	0%	-19%	119%
25th Quantile	-0,057	1%	-24%	123%
50th Quantile	-0,048	-1%	-6%	106%
75th Quantile	-0,050	-10%	-42%	152%
90th Quantile	-0,070	0%	-43%	143%

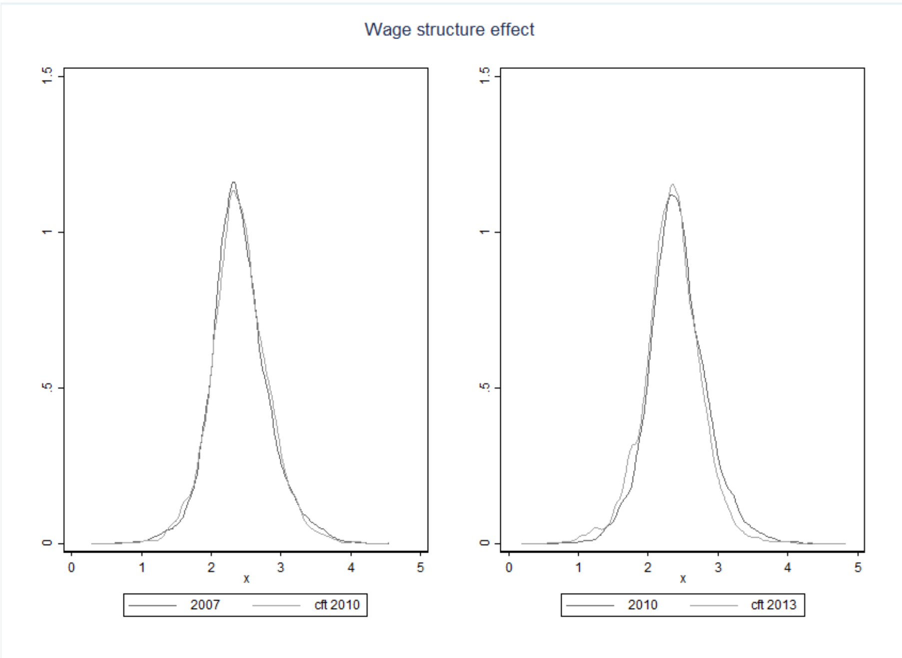

Figure 4.3: Effect of Wage structure for the periods 2007-2010 and 2010-2013

even though it is still not clear what are the mechanisms underlying this relationship. Indeed we showed how much each factor accounts in the changes of our outcome variable of interest and we gave an indication about which explanations are to be explored in more detail. However future work is required to better clarify the reasons underneath such explanations. Second, a sort of segmentation of wages may have occurred since the Great recession is having different impacts on wages both between groups and along the distribution. Castellano et al. (2017) suggest job-polarisation as an explanation while Arestis et al. (2013) suggest that this stratification effect is at least in part the long-run outcome of structural processes generated by the financialization process occurred in our economies. Wages inequalities then seems depends on social institutions and on the structure of the financial system. These findings have important implications for economic and social policy. In light of these reflections it seems foremost important to stress that only a strong bargaining power of workers can ensure the proper wage adjustments and proper measures should be taken in consideration to ensure that the lessen employment protection legislations and the new contractual forms are not preventing this from happening. Indeed Arpaia & Curci (2010) expect the growth in the unit labour cost to be more moderate if new negotiated wages start to incorporate the effect of the recession and productivity growth recovers. Both Francese & Mulas-Granados (2015) and Stockhammer (2013) suggests also that strengthening the welfare state, in particular changing union legislation to foster collective bargaining, and financial regulation could help increase the wage share and decrease inequality.

Conclusions

The traditional approach to social programme evaluation has been centred on estimating mean impacts. However the growing interest in the evaluation literature for models that are informative on the impact among the entire distribution of an outcome has brought more deep understanding of how public policies and social interventions affects the population. Indeed impact evaluation exercises can have strong impact on reality and for this reason methodological improvements are necessary to better disentangle what affects the outcomes in order to give policy makers the best tools to make informed and relevant decisions. Among theses tools the estimation of counterfactual distributions and decomposition methods have been predominant techniques. More in detail, in this work we have addressed an empirical economic issue that has been of great relevance for Italy in the last decades, namely the change occurred in wage distributions of workers and the consequent increase of wage inequalities. We analysed three possible sources of variation using data from EU-SILC databases of 2007 and 2013. The first one regards a change in the labour market institutions that concerns the introduction and spread of new forms of flexible, more precarious job contracts. Secondly we took in consideration changes in the personal characteristics of workers and thirdly we looked into structural changes that occurred because of the Great Recession. We discussed what structural changes mean and may imply in term of wage dynamic to provide a meaningful interpretation of the residual component of the decomposition. From this complex elaboration of data it is possible to draws some final remarks and policy recommendations.

From a methodological point of view we presented two contributions. First of all we presented a review of the most recent techniques to evaluate effects among the entire distribution of an outcome variable of interest. Secondly we have implemented the solid and well know technique developed by DiNardo et al. (1996) into the context of the Italian Labour Market that, to my knowledge, has never been done. This semi-parametric technique recreates different counterfactual distributions through a Kernel estimation over a properly re-weighted sample, allowing for causal interpretation. This flexible approach was used to decompose unconditional wage differentials and calculate measures of inequalities in different but connected scenarios. Differently from former decomposition works, the residual factor is our main interest since, under proper independence assumptions, represents the measure of the impact we are inquiring.

Regarding the the empirical contribution of the work, first we decomposed the difference in wages for to groups of workers under different working agreements, respectively temporary and permanent contracts. In line with previous findings the distribution of wages for temporary contracts is lower at each quantile and both the personal attributes and the residual part contribute to lower the distribution. However while there is a difference in salaries due to differences in personal endowments, temporary contracts suffer of a wage discrimination and this discrimination in concentrated at the bottom of the distribution, especially for 2013. The decrease in the strength of employment protection legislations occurred only for this type of contracts, eroding the bargaining power of job-seekers, keeping them into low paid and low skilled jobs (sticky floor effect), facing a higher risk of systematically lower wages and more instability. From the sub-group analysis we found that while for men the sticky floor effect is valid, women present a wage discrimination more spread across the distribution. Low skilled workers and younger people are the groups who suffer the most from this wage discrimination. From a geographical point of view, while the northern and central regions present a wage penalty at the bottom of the distribution, the South of Italy suffers more of a glass ceiling effect in which temporary workers are paid less then their counterparts especially in the high-paid jobs. Literature suggests that wage discrimination based on working agreements might concur in increasing the job polarisation of the market.

Secondly we decomposed the changes in wage distributions across time to capture the structural evolution of the labour market due to the Great Recession of 2008/2009. The results show that the way jobs are rewarded followed a decreasing path and the residual factor explains the majority of the ”stickness” (Arpaia & Curci, 2010) of salaries, while the increase of temporary contracts has a residual effect and other job-related characteristics have a positive impact. Also this second result is in line with previous theory that conjectures a less efficient structure in rewarding skills and creating appropriate job opportunities. Women, young and low skilled workers seem to be the most affected categories. This might be a further suggestion that the structure of the labour market is in fact polarising. Moreover Stockhammer (2013) suggests that also financialisation has a role in explaining the lack of increase in wages in the last period since it affect the bargaining position of labour (along with globalisation, technological change and decline in welfare state funding). To draw some conclusions we showed how much each of the factors took in consideration accounts in the changes of our outcome variable of interest. The decrease in real wages caused by the Great Recession is in line with previous findings even though what are the mechanisms underlying this relationship is still a topic of debate. Indeed we gave an indication about which explanations are to be explored in more detail. However future work is required to better clarify the reasons underneath such explanations. A sort of segmentation of wages may have occurred since the Great recession is having different impacts on wages both between groups and along the distribution. Castellano et al. (2017) suggest job-polarisation as an explanation while Arestis et al. (2013) suggest that this stratification effect is at least in part the long-run outcome of structural processes generated by the financialization process occurred in our economies. Wages inequalities then seems depends on social institutions and on the structure of the financial system. These findings have important implications for economic and social policy. In light of these reflections it seems foremost important to stress that only a strong bargaining power of workers aimed to improve labour conditions and decrease the precariousness of career paths especially for the young and low skilled cohorts can ensure the proper wage adjustments. Measures should be taken in consideration to ensure that the lessen employment protection legislations and the new contractual forms are not preventing this from happening. Indeed Arpaia & Curci (2010) expect the growth in the unit labour cost to be more moderate if new negotiated wages start to incorporate the effect of the recession and productivity growth recovers. Both Francese & Mulas-Granados (2015) and Stockhammer (2013) suggests also that strengthening the welfare state, in particular changing union legislation to foster collective bargaining, and financial regulation could help increase the wage share and decrease inequality.

Appendix A: Wage penalty for sub-groups of workers

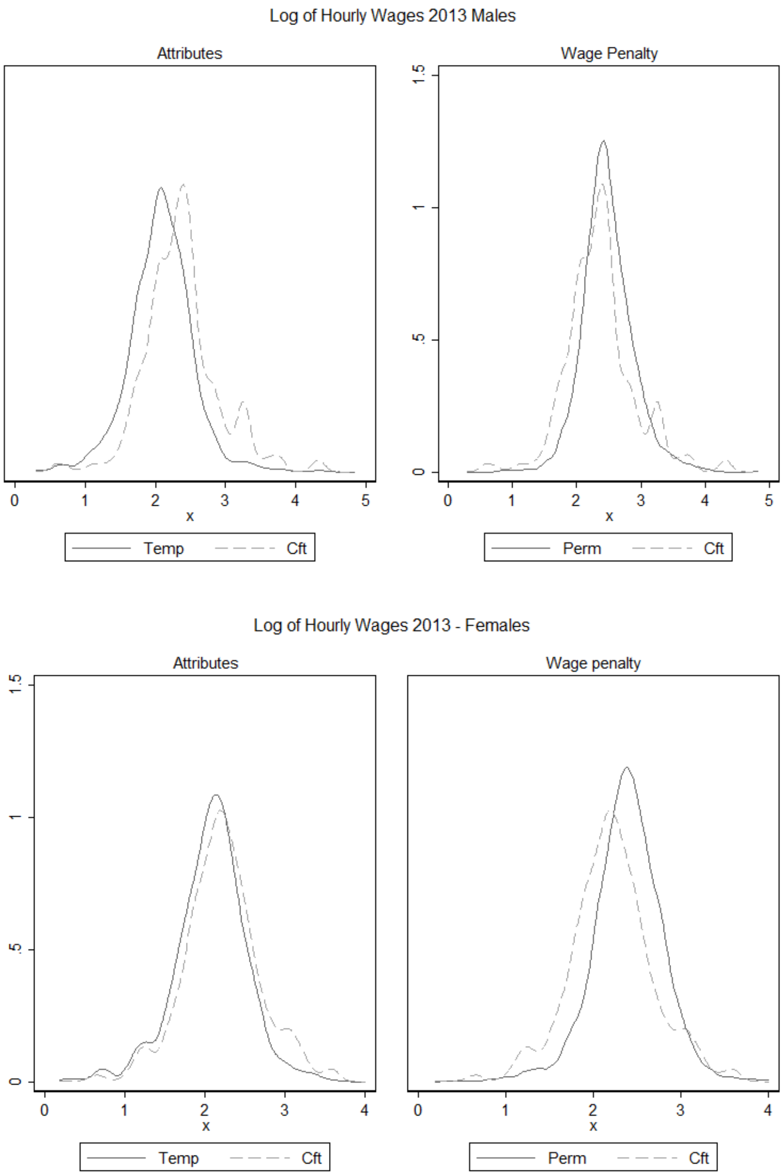

Figure 4: Decomposition of Wage Distribution 2013 by Gender

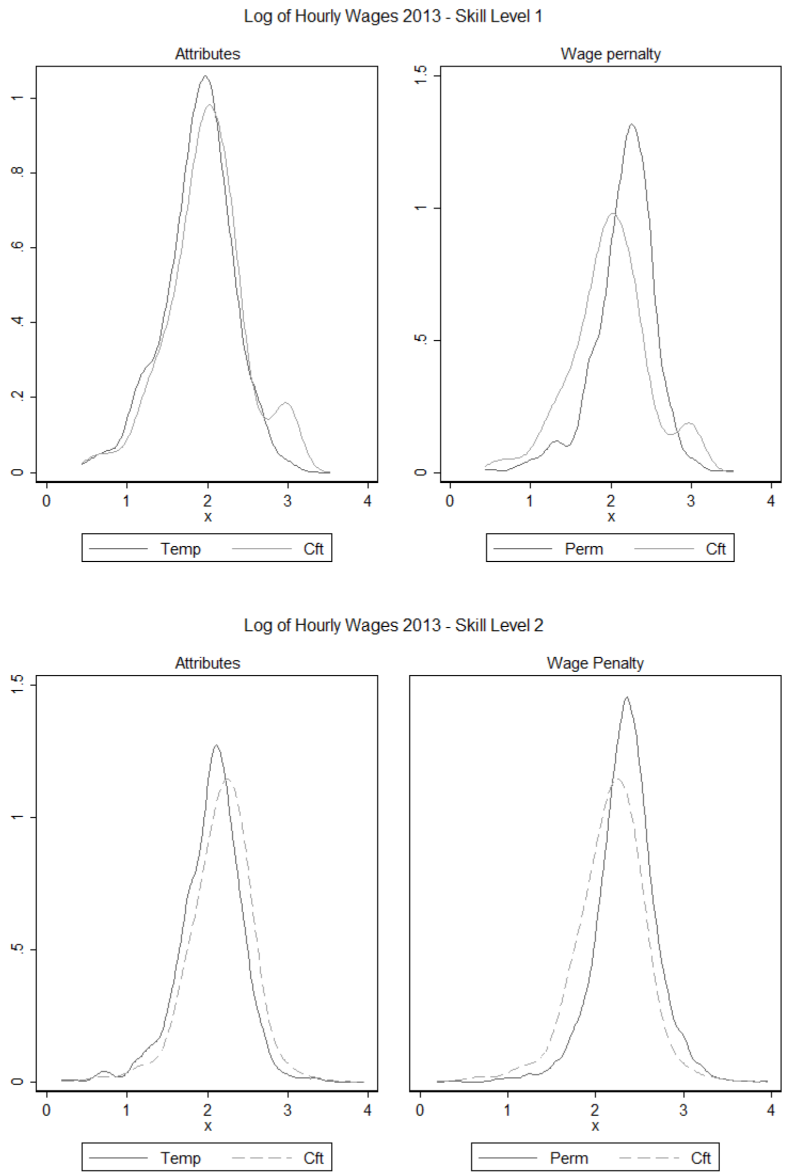

Figure 5: Decomposition of Wage Distribution 2013 by Skill Level 1 and 2

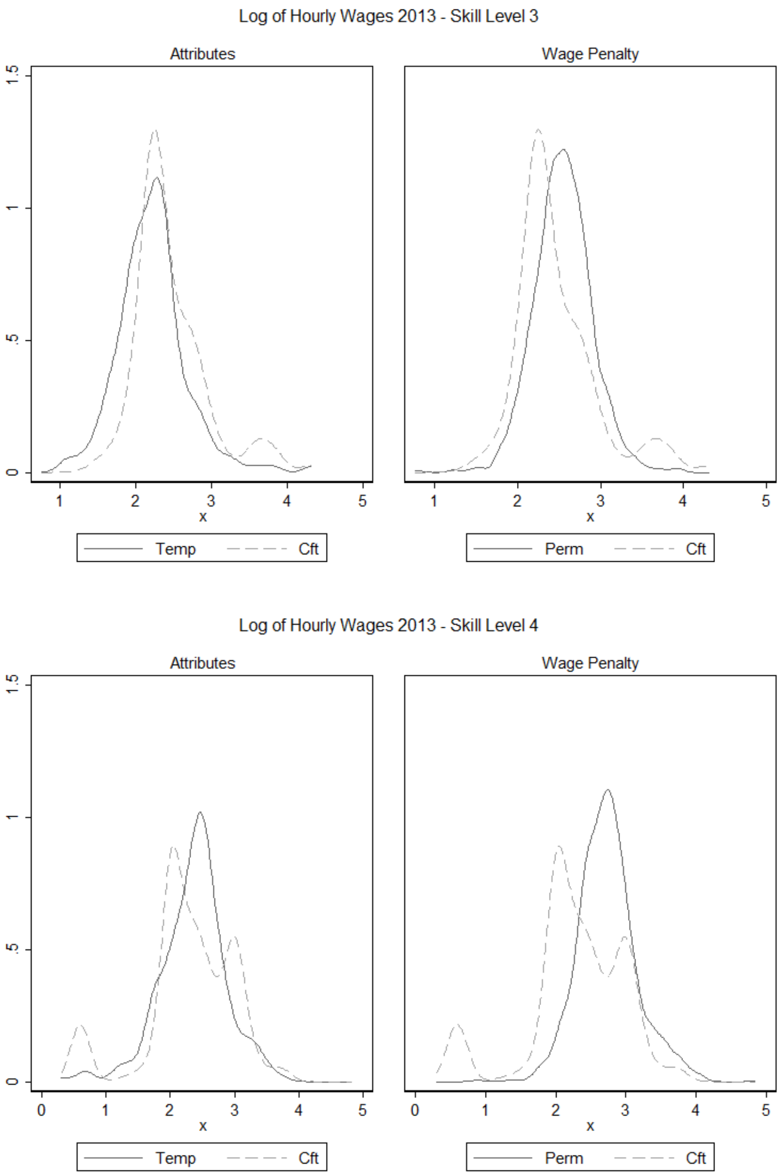

Figure 6: Decomposition of Wage Distribution 2013 by Skill Level 3 and 4

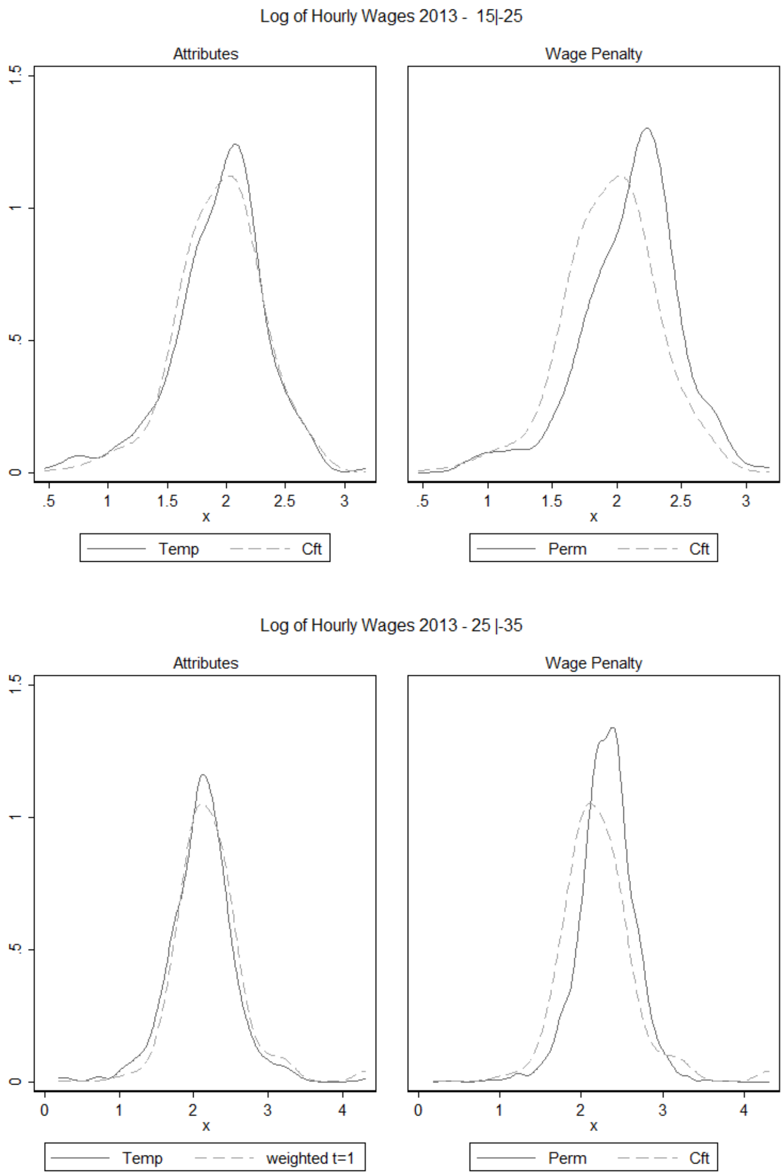

Figure 7: Decomposition of Wage Distribution 2013 by Age Class 15-25 and 25-35

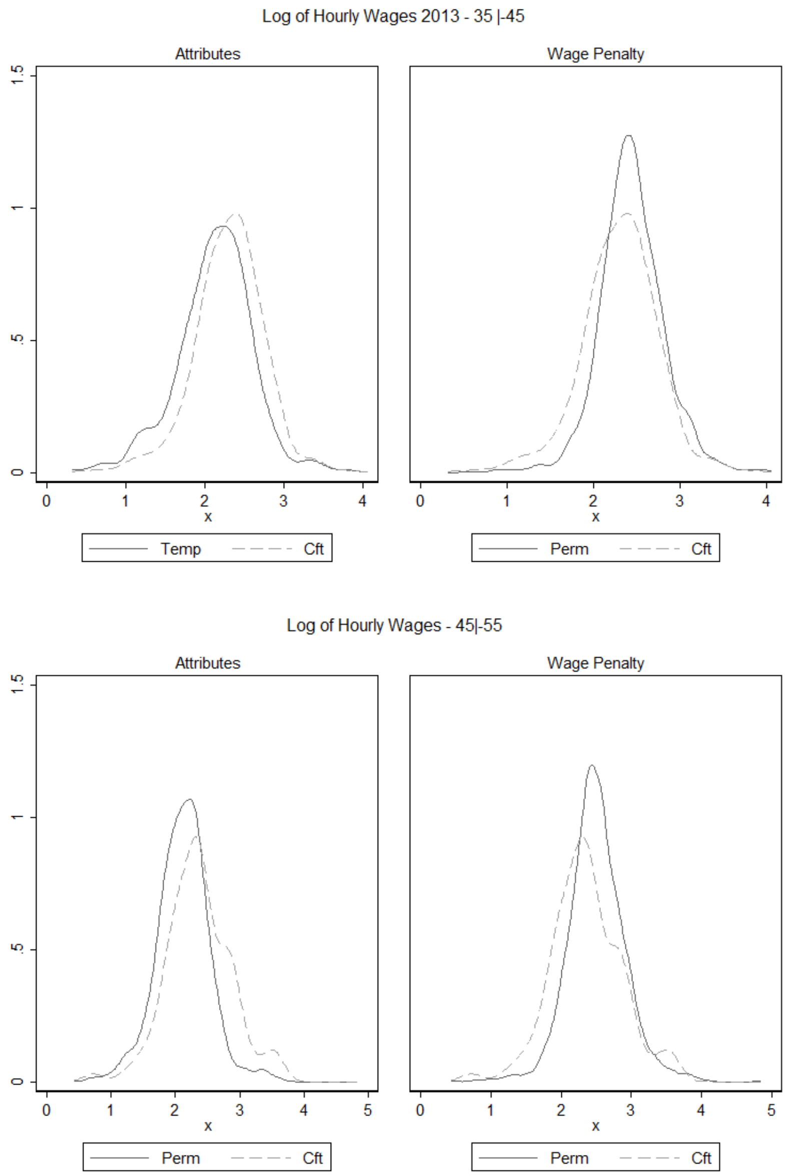

Figure 8: Decomposition of Wage Distribution 2013 by Age Class 35-45 and 45-55

Figure 9: Decomposition of Wage Distribution 2013 by Age Class 55-65

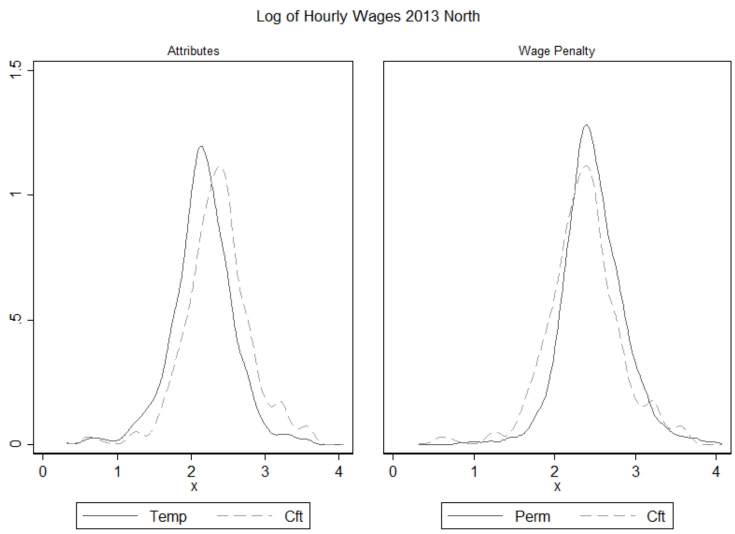

Figure 10: Decomposition of Wage Distribution 2013 by Region

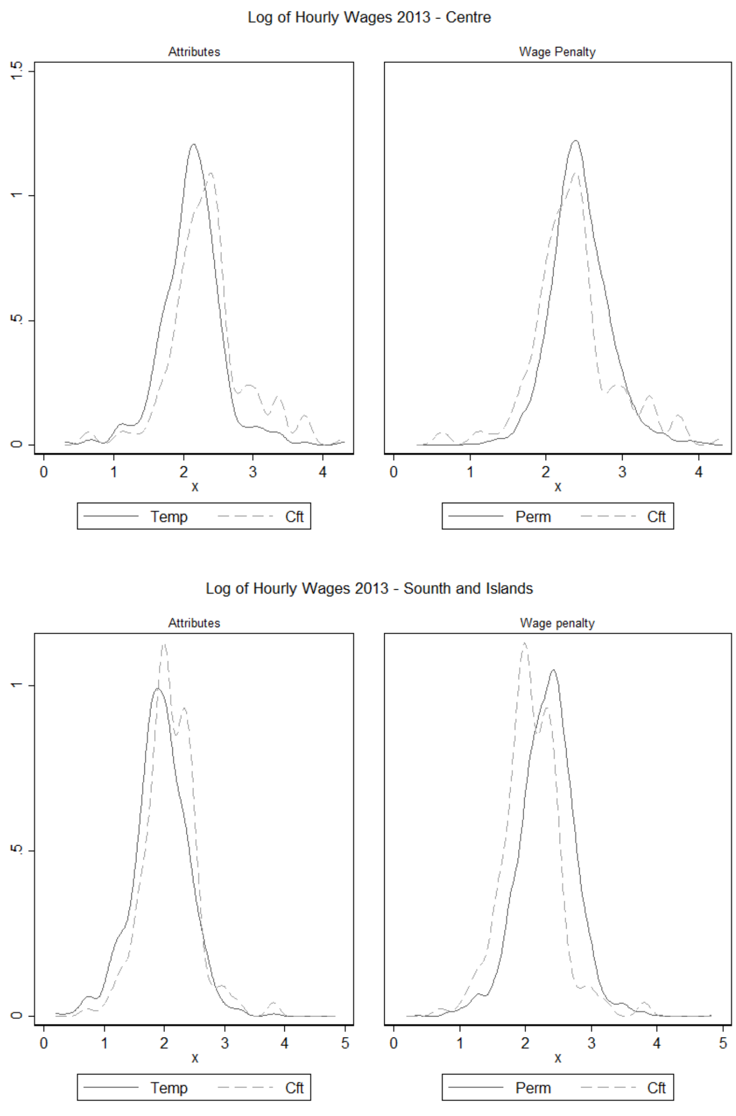

Figure 11: Decomposition of Wage Distribution 2013 by Region

Appendix B: Decomposing Changes in Wage Distribution Across Time for Sub-Groups

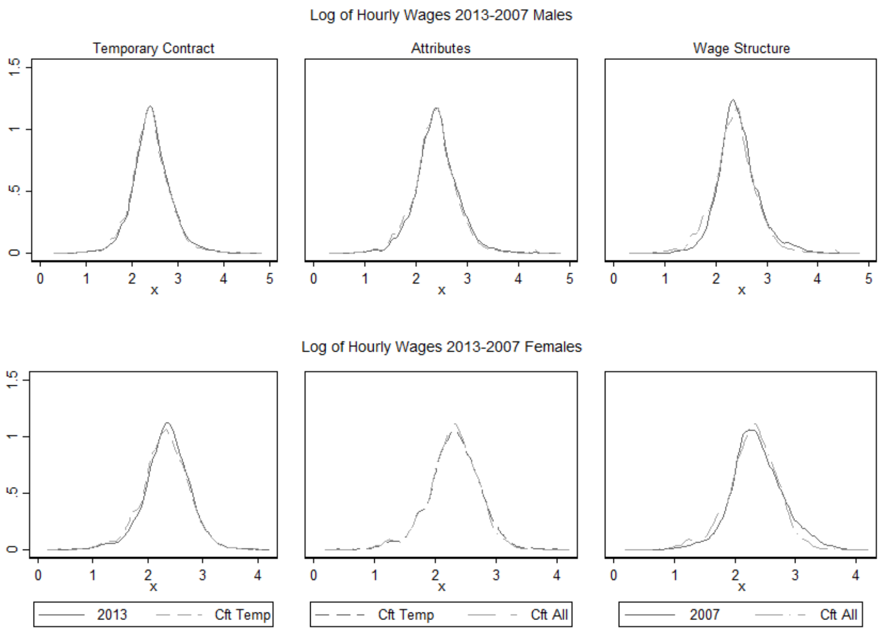

Figure 12: Decomposition of Wage Distribution 2013-2007 By Gender

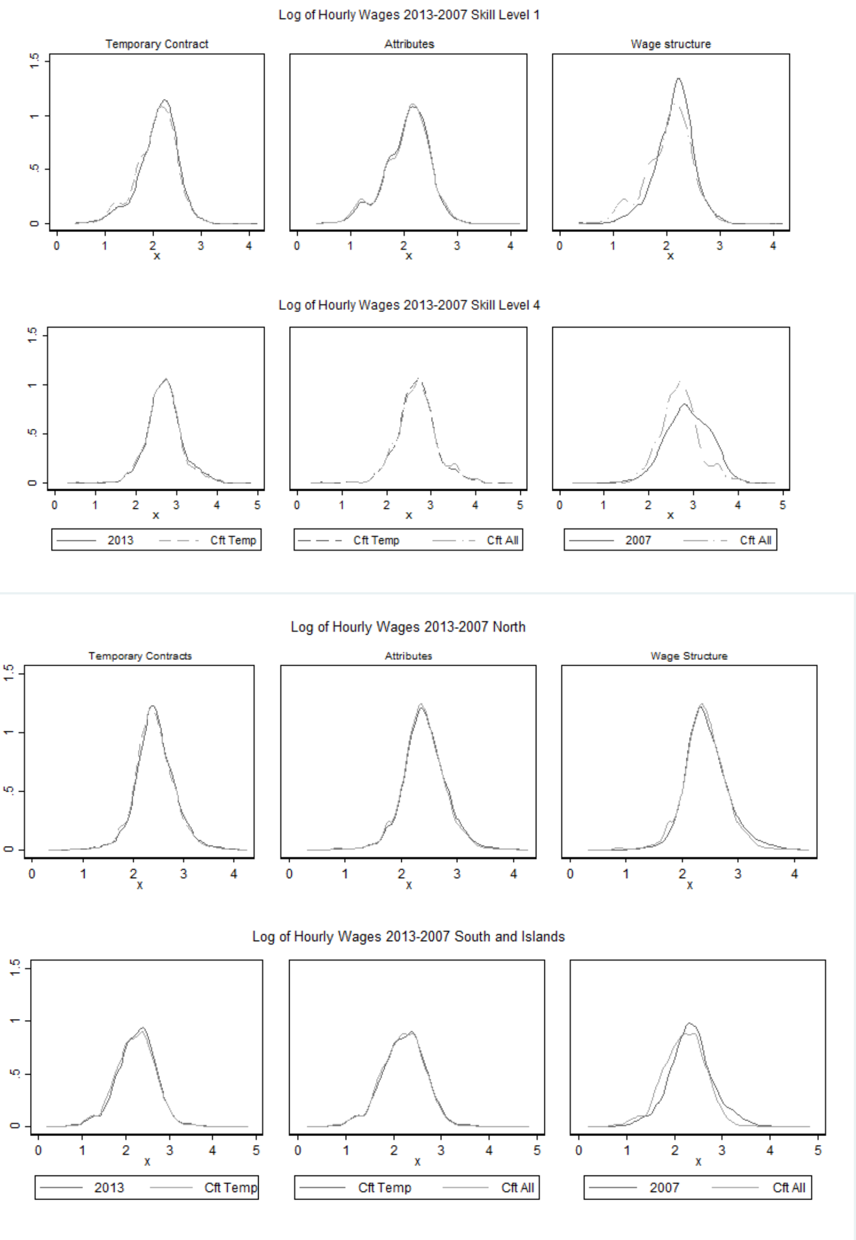

Figure 13: Decomposition of Wage Distribution 2013-2007 by Skills and Regions

Appendix C: List of Covariates

Dummy Name	Description	ISCO 88/08 code	
Skill Level 1	Elementary Occupations	9	
	Plant and machine operators, and assemblers	8	
	Craft and related trades workers	7	
Skill Level 2	Skilled agricultural and fishery workers	6	
	Service and sales workers	5	
	Clerks	4	
Skill Level 3	Technicians and associate professionals	3	
Skill Level 4	Professionals and Managers	2 and 1	
		ISCED code	
Low Education Level	Pre-primary and Primary Education	ISCED 0 - 1	
Medium Education Level	Lower, Upper Secondary Education and Post Secondary Education	ISCED 2 - 4	
High Education Level	1st and 2nd Level of Tertiary Education	ISCED 5 - 8	
		NACE 2 code	NACE 1.1 code
Nace 1	Agriculture, hunting and forestry and fishing	a	a - b
Nace 2	Mining, quarrying, Manifacturing, Electricity	b - e	c - e
Nace 3	Construction	f	f
Nace 4	Wholesale and retail trade	g	g
Nace 5	Hotels and restaurants	i	h
Nace 6	Transport, storage and communications	h - j	i
Nace 7	Financial intermediation	k	j
Nace 8	Real estate, renting and business activities	l - n	k
Nace 9	Public Administration, Defense	o	l
Nace 10	Education	p	m
Nace 11	Health and social Network	q	n
Nace 12	Other community, social and personal services	r-u	o -q

Name	Code	Description	EU-SILC primary variable
Log of Houry Wages	#	Amount before tax and social insurance contributions deduction, deflated with FOI	py200G and pl060
Temporary	1	Temporary job/work contract of limited duration	pl140
	0	Permanent job/work contract of unlimited duration	
Sex	1	Male	rb090
	0	Female	
Full Time	1	Employed/Self Employed working full time	pl030 for 2007 and pl031 for 2013
	0	Employed/Self Employed working part time	
Immigrant	1	Italian (1st citizenship)	pb220a
	0	Not Italian (1st citizenship)	
Ageclass[12]	1	15 -| 25	rx020
	2	25 -| 35	
	3	35 -| 45	
	4	45 -| 55	
	5	55 -| 65	
Managerial position	1	Supervisory	pl150
	0	Not Supervisory	
Experience	#	the number of years since the respondent started their first regular job	pl200
Local unit[13]	1	Persons working at local unit between 1 and 10	pl130
	2	Persons working at local unit between 11 and 50	
	3	Persons working at local unit more than 50	
Marital Status[14]	1	Never Married	pb190
	2	Married	
	3	Once Married (Separated, Widowed, Divorced)	
Child	#	Number of children under 18 in HH	
Region[15]	1	North-West	db040
	2	South	
	3	Islands	
	4	North-East	
	5	Centre	

Bibliography

Abadie, Alberto, & Cattaneo, Matias D. 2018. Econometric methods for program evaluation. Annual review of economics, 10(1), 465–503.

Abadie, Alberto, Angrist, Joshua, & Imbens, Guido. 2002. Instrumental variables estimates of the effect of subsidized training on the quantiles of trainee earnings. Econometrica, 70(1), 91–117.

Abrevaya, Jason, & Dahl, Christian M. 2008. The effects of birth inputs on birthweight. Journal of business & economic statistics, 26(4), 379–397.

Acemoglu, Daron, & Autor, David. 2011. Skills, Tasks and Technologies: Implications for Employment and Earnings. Handbook of Labor Economics, vol. 4. Elsevier. Chap. 12, pages 1043–1171.

Angrist, Joshua, & Krueger, Alan. 1999. Empirical strategies in labor economics. Chap. 23, pages 1277–1366 of: Ashenfelter, O., & Card, D. (eds), Handbook of labor economics, 1 edn., vol. 3, Part A. Elsevier.

Angrist, Joshua, & Pischke, Jorn-Steffen. 2009. Mostly harmless econometrics: An empiricist's companion. 1 edn. Princeton University Press.

Angrist, Joshua, Chernozhukov, Victor, & Fernández-Val, Iván. Quantile regression under misspecification, with an application to the u.s. wage structure. Econometrica, 74(2), 539–563.

Angrist, Joshua D. 2004. Treatment effect heterogeneity in theory and practice*. The economic journal, 114(494), C52–C83.

Arestis, Philip, Charles, Aurélie, & Fontana, Giuseppe. 2013. Financialization, the great recession, and the stratification of the us labor market. Feminist economics, 19(3), 152–180.

Argitis, Georgios, & Pitelis, Christos. 2001. Monetary policy and the distribution of income: Evidence for the united states and the united kingdom. Journal of post keynesian economics, 23(4), 617–638.

Arpaia, Alfonso, & Curci, Nicola. 2010. Eu labour market behaviour during the great recession. European Economy - Economic Papers 2008 - 2015 405. Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Ashenfelter, O., & Card, D. (eds). 2011. Copyright. Handbook of Labor Economics, vol. 4. Elsevier.

Atkinson, Anthony B. 1970. On the measurement of inequality. Journal of economic theory, 2(3), 244 – 263.

Autor, David H., Katz, Lawrence F., & Kearney, Melissa S. 2005. Rising wage inequality: The role of composition and prices. NBER Working Papers 11628. National Bureau of Economic Research, Inc.

Ballestrero, Vittoria M., & De Simone, Gisella. 2012. Diritto del lavoro. Giappichelli.

Barany, Zsofia, & Siegel, Christian. 2015 (July). Job Polarization and Structural Change. Sciences Po Economics Discussion Papers 2015-07. Sciences Po Departement of Economics.

Bentolila, Samuel, Cahuc, Pierre, Dolado, Juan J., & Le Barbanchon, Thomas. 2012. Two-tier labour markets in the great recession: France versus spain. The economic journal, 122(562).

Bernhardt, Annette. 2014. Labor standards and the reorganization of work: Gaps in data and research. Institute for research on labor and employment, working paper series. Institute of Industrial Relations, UC Berkeley.

Bhalotra, Sonia, & Manuel, FernÃ¡ndez. 2018. The distribution of the gender wage gap. ISER Working Paper Series 2018-10. Institute for Social and Economic Research.

Biewen, Martin, & Jenkins, Stephen. 2005. A framework for the decomposition of poverty differences with an application to poverty differences between countries. Empirical economics, 30(2), 331–358.

Bitler, Marianne P., Gelbach, Jonah B., & Hoynes, Hilary W. 2006. What mean impacts miss: Distributional effects of welfare reform experiments. American economic review, 96(4), 988–1012.

Bitler, Marianne P., Gelbach, Jonah B., & Hoynes, Hilary W. 2008. Distributional impacts of the self-sufficiency project. Journal of public economics, 92(3-4), 748–765.

Blinder, Alan S. 1973. Wage discrimination: Reduced form and structural estimates. The journal of human resources, 8(4), 436–455.

Blundell, Richard, Gosling, Amanda, Ichimura, Hidehiko, & Meghir, Costas. Changes in the distribution of male and female wages accounting for employment composition using bounds. Econometrica, 75(2), 323–363.

Boeri, Tito. 2011. Institutional reforms and dualism in european labor markets. 1 edn., vol. 4B. Elsevier.

Bolelli, Monica. 2017. Dualization vs. solidarity: the role of italian unions in the restructuring of the welfare state. M.Phil. thesis, University of Amsterdam, The Netherlands.

Bosio, Giulio. 2013. The implications of temporary jobs on the distribution of wages in italy: An unconditional ivqte approach. Labour, 28(1), 64–86.

Buchinsky, Moshe. 1994. Changes in the u.s. wage structure 1963-1987: Application of quantile regression. Econometrica, 62(2), 405–458.

Card, David. 1996. The effect of unions on the structure of wages: A longitudinal analysis. Econometrica, 64(4), 957–79.

Card, David, & DiNardo, John E. 2002. Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles. Journal of labor economics, 20(4), 733–783.

Castellano, Rosalia, Musella, Gaetano, & Punzo, Gennaro. 2017. Structure of the labour market and wage inequality: evidence from european countries. Quality & quantity, 51(5), 2191–2218.

Chernozhukov, Victor, Fernández-Val, Iván, & Melly, Blaise. 2013. Inference on counterfactual distributions. Econometrica, 81(6), 2205–2268.

Colella, Fabrizio. 2014. Women's part-time - full-time wage differentials in europe: an endogenous switching model. MPRA Paper 55287. University Library of Munich, Germany.

Comi, Simona, & Grasseni, Mara. 2012. Are temporary workers distriminated against? evidence from europe. The manchester school, 80(1), 28–50.

Commission, European. 2006a. Labour market and wage developments in 2006. Tech. rept. European Commission, EU.

Commission, European. 2006b. Modernising labour law to meet the challenges of the 21st century. Tech. rept. European Commission, EU.

Commission, European. 2013a. Employment and social developments in europe 2013. Tech. rept. European Comminsion.

Commission, European. 2013b. Labour market and wage developments in 2013. Tech. rept. European Commission, EU.

Commission, European. 2013c. Precarious employment in europe: Patterns, trends and policy strategies. Tech. rept. European Commission, EU.

Cotton, Jeremiah. 1988. On the decomposition of wage differentials. The review of economics and statistics, 70(2), 236–243.

Dammert, Ana C. 2008. Heterogeneous impacts of conditional cash transfers: Evidence from nicaragua. IZA Discussion Papers 3653. Institute for the Study of Labor (IZA).

Deaton, Angus. 2010. Instruments, randomization, and learning about development. Journal of economic literature, 48(2), 424–55.

Dhaene, J., Denuit, M., Goovaerts, M.J., Kaas, R., & Vyncke, D. 2002. The concept of comonotonicity in actuarial science and finance: theory. Insurance: Mathematics and economics, 31(1), 3 – 33.

DiNardo, John. 2002. Propensity score reweighting and changes in wage distributions. University of Michigan and NBER.

DiNardo, John, Fortin, Nicole M., & Lemieux, Thomas. 1996. Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. Econometrica, 64(5), 1001–1044.

Djebbari, Habiba, & Smith, Jeffrey. 2008. Heterogeneous impacts in progresa. Journal of econometrics, 145(1), 64 – 80.

Donald, Stephen G., Green, David A., & Paarsch, Harry J. 2000. Differences in wage distributions between canada and the united states: An application of a flexible estimator of distribution functions in the presence of covariates. The review of economic studies, 67(4), 609–633.

Duménil, Gérard, & Lévy, Dominique. 2001. Costs and benefits of neoliberalism. a class analysis. Review of international political economy, 8(4), 578–607.

Elder, Todd, Goddeeris, John, & Haider, Steven. 2010. Unexplained gaps and oaxaca-blinder decompositions. Labour economics, 17(1), 284–290.

Elder, Todd E., Goddeeris, John H., & Haider, Steven J. 2015. Isolating the roles of individual covariates in reweighting estimation. Journal of applied econometrics, 30(7), 1169–1191.

Elsby, Michael W. L., Shin, Donggyun, & Solon, Gary. 2016. Wage adjustment in the great recession and other downturns: Evidence from the united states and great britain. Journal of labor economics, 34(S1), S249–S291.

Essama-Nssah, B., & Lambert, Peter J. 2011. Influence functions for distributional statistics. Working Papers 236. ECINEQ, Society for the Study of Economic Inequality.

Eurostat. 2018. European union statistics on income and living conditions.

Fan, Jianqing, & Gijbels, Irene. 1996. Local polynomial modelling and its applications. Chapman and Hall/CRC.

Ferraro, Paul, & Miranda, Juan Jose. 2013. Heterogeneous treatment effects and mechanisms in information-based environmental policies: Evidence from a large-scale field experiment. Resource and energy economics, 35(3), 356–379.

Firpo, Sergio. 2007. Efficient semiparametric estimation of quantile treatment effects. Econometrica, 75(1), 259–276.

Firpo, Sergio, Fortin, Nicole M., & Lemieux, Thomas. 2009. Unconditional quantile regressions. Econometrica, 77(3), 953–973.

Fort, Margherita. 2012. Unconditional and conditional quantile treatment effect: Identification strategies and interpretations. Working paper 857.

Fortin, Nicole. 2008. The gender wage gap among young adults in the united states: The importance of money versus people. Journal of human resources, 43(4).

Fortin, Nicole, Lemieux, Thomas, & Firpo, Sergio. 2011. Chapter 1 - decomposition methods in economics. Handbook of Labor Economics, vol. 4. Elsevier.

Francese, Maura, & Mulas-Granados, Carlos. 2015. Functional income distribution and its role in explaining inequality. IMF Working Papers 15/244. International Monetary Fund.

Frölich, M., & Melly, B. 2010. Estimation of quantile treatment effects with stata. Stata journal, 10(3), 423–457(35).

Frölich, Markus. 2007. Propensity score matching without conditional independence assumption—with an application to the gender wage gap in the united kingdom. The econometrics journal, 10(2), 359–407.

Frölich, Markus, & Melly, Blaise. 2013. Unconditional quantile treatment effects under endogeneity. Journal of business & economic statistics, 31(3), 346–357.

Galvao, Antonio F., Lamarche, Carlos, & Lima, Luiz Renato. 2013. Estimation of censored quantile regression for panel data with fixed effects. Journal of the american statistical association, 108(503), 1075–1089.

Garofalo, Antonio, Castellano, Rosalia, Punzo, Gennaro, & Musella, Gaetano. 2018. Skills and labour incomes: how unequal is Italy as part of the Southern European countries? Quality & quantity: International journal of methodology, 52(4), 1471–1500.

Geraci, Marco, & Bottai, Matteo. 2007. Quantile regression for longitudinal data using the asymmetric laplace distribution. Biostatistics, 8(1), 140–154.

Gérard, Duménil, & Dominique, Lévy. 2004. Capital resurgent: Roots of the neoliberal revolution. Harvard University Press.

Goedemé, Tim. 2010. The standard error of estimates based on eu-silc. an exploration through the europe 2020 poverty indicators. Tech. rept. WP 10/09. Herman Deleeck Centre for Social Policy, University of Antwerp.

Goedemé, Tim. 2013. How much confidence can we have in eu-silc? complex sample designs and the standard error of the europe 2020 poverty indicators. Social indicators research, 110(1), 89–110.

Goldin, Claudia, & Katz, Lawrence. 2007. The race between education and technology: The evolution of u.s. educational wage differentials, 1890 to 2005. NBER Working Papers 12984. National Bureau of Economic Research, Inc.

Goos, Maarten, & Manning, Alan. 2007. Lousy and lovely jobs: The rising polarization of work in britain. The review of economics and statistics, 89(1), 118–133.

Goos, Maarten, Manning, Alan, & Salomons, Anna. 2014. Explaining job polarization: Routine-biased technological change and offshoring. American economic review, 104(8), 2509–26.

Gosling, Amanda, Machin, Stephen, & Meghir, Costas. 2000. The changing distribution of male wages in the u.k. The review of economic studies, 67(4), 635–666.

Gramacki, Artur. 2018. Nonparametric kernel density estimation and its computational aspects. Springer International Publishing.

Heckman, James, LaLonde, Robert, & Smith, Jeffrey. 1999. The economics and econometrics of active labor market programs. Chap. 31, pages 1865–2097 of: Ashenfelter, O., & Card, D. (eds), Handbook of labor economics, 1 edn., vol. 3, Part A. Elsevier.

Heckman, James J. 2008. Econometric causality. International statistical review, 76(1), 1–27.

Heckman, James J., Smith, Jeffrey, & Clements, Nancy. 1997. Making the most out of programme evaluations and social experiments: Accounting for heterogeneity in programme impacts. The review of economic studies, 64(4), 487–535.

Hein, Eckhard, & Schoder, Christian. 2011. Interest rates, distribution and capital accumulation – a post-kaleckian perspective on the us and germany. International review of applied economics, 25(6), 693–723.

Henderson, Daniel, Polachek, Solomon, & Wang, Le. 2011. Heterogeneity in schooling rates of return. IZA Discussion Papers 5662. Institute for the Study of Labor (IZA).

Henderson, Daniel J., Olbrecht, Alexandre, & Polachek, Solomon W. 2006. Do former college athletes earn more at work? a nonparametric assessment. The journal of human resources, 41(3), 558–577.

Hirano, Keisuke, Imbens, Guido W., & Ridder, Geert. 2003. Efficient estimation of average treatment effects using the estimated propensity score. Econometrica, 71(4), 1161–1189.

Holland, Paul W. 1986. Statistics and causal inference. Journal of the american statistical association, 81(396), 945–960.

Hu, Anning, & Hibel, Jacob. 2015. Increasing heterogeneity in the economic returns to higher education in urban china. The social science journal, 52(3), 322 – 330.

ILO. 2008. World of work report 2008. income inequalities in the age of financial globalization. Tech. rept. ILO:Geneve.

ILO. 2011. International standard classification of occupations structure, group defi nitions and correspondence tables.

Imai, Kosuke, & Ratkovic, Marc. 2013. Estimating treatment effect heterogeneity in randomized program evaluation. 7(1), 443–470.

Imbens, Guido W., & Angrist, Joshua D. 1994. Identification and estimation of local average treatment effects. Econometrica, 62(2), 467–475.

Imbens, Guido W., & Newey, Whitney K. Identification and estimation of triangular simultaneous equations models without additivity. Econometrica, 77(5), 1481–1512.

Imbens, Guido W., & Rubin, Donald B. 2015. Causal inference for statistics, social, and biomedical sciences: An introduction. Cambridge University Press.

Imbens, Guido W., & Wooldridge, Jeffrey M. 2009. Recent developments in the econometrics of program evaluation. Journal of economic literature, 47(1), 5–86.

Jackson, Erika, & Page, Marianne. 2013. Estimating the distributional effects of education reforms: A look at project star. Economics of education review, 32(C), 92–103.

Jann, B. 2008a. The blinder-oaxaca decomposition for linear regression models. Stata journal, 8(4), 453–479(27).

Jann, B. 2008b. The blinder-oaxaca decomposition for linear regression models. Stata journal, 8(4), 453–479(27).

John Black, Nigar Hashimzade, & Myles, Gareth. 2009. A dictionary of economics. Oxford University Press.

Johns, Merida. 2013. Breaking the glass ceiling: Structural, cultural, and organizational barriers preventing women from achieving senior and executive positions. Perspectives in health information management / ahima, american health information management association, 10(01), 1e.

Juhn, Chinhui, Murphy, Kevin M., & Pierce, Brooks. 1993. Wage inequality and the rise in returns to skill. Journal of political economy, 101(3), 410–442.

Katz, Lawrence, & Autor, David. 1999. Changes in the wage structure and earnings inequality. Chap. 26, pages 1463–1555 of: Ashenfelter, O., & Card, D. (eds), Handbook of labor economics, 1 edn., vol. 3, Part A. Elsevier.

Katz, Lawrence F., & Krueger, Alan B. 2016. The rise and nature of alternative work arrangements in the united states, 1995-2015. Working Papers 603. Princeton University, Department of Economics, Industrial Relations Section.

Khandker, Shahidur R., Koolwal, Gayatri B., & Samad, Hussain A. 2009. Handbook on impact evaluation : quantitative methods and practices. The World Bank.

Kim, ChangHwan. 2010. Decomposing the change in the wage gap between white and black men over time, 1980-2005: An extension of the blinder-oaxaca decomposition method. Sociological methods & research, 38(4), 619–651.

Kline, Patrick. 2011. Oaxaca-blinder as a reweighting estimator. American economic review, 101(3), 532–37.

Koenker, Roger. 2005. Quantile regression. Econometric Society Monographs.

Koenker, Roger, & Bassett, Gilbert. 1982. Robust tests for heteroscedasticity based on regression quantiles. Econometrica, 50(1), 43–61.

Koenker, Roger, & Hallock, Kevin F. 2001. Quantile regression. Journal of economic perspectives, 15(4).

Koenker, Roger, & Machado, Jose A. F. 1999. Goodness of fit and related inference processes for quantile regression. Journal of the american statistical association, 94(448), 1296–1310.

Koenker, Roger W, & Bassett, Gilbert. 1978. Regression quantiles. Econometrica, 46(1), 33–50.

Kunze, Astrid. 2005. The evolution of the gender wage gap. Labour economics, 12(1), 73–97.

Lamarche, Carlos. 2011. Measuring the incentives to learn in colombia using new quantile regression approaches. Journal of development economics, 96(2), 278–288.

Lazonick, William, & O'Sullivan, Mary. 2000. Maximizing shareholder value: a new ideology for corporate governance. Economy and society, 29(1), 13–35.

Lemieux, T. 2002. Decomposing changes in wage distributions: A unified approach [la décomposition des changements dans les distributions de salaires : Une approche unifée]. Canadian journal of economics, 35(4), 646–688.

Lemieux, Thomas. 2006. Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill? American economic review, 96(3), 461–498.

Li, Qi, & Racine, Jeffrey. 2006. Nonparametric econometrics: Theory and practice. 1 edn. Princeton University Press.

M. Andersen, Torben. 2011. A flexicurity labour market in the great recession: The case of denmark. De economist, 160(05).

Machado, José A. F., & Mata, José. 2005. Counterfactual decomposition of changes in wage distributions using quantile regression. Journal of applied econometrics, 20(4), 445–465.

Machado, José A. F., & Silva, João M. S. 2013. Quantile regression and heteroskedasticity.

Magnani, Elisabetta, & Zhu, Rong. 2012. Gender wage differentials among rural–urban migrants in china. Regional science and urban economics, 42(5), 779–793.

Martins, Pedro S., Solon, Gary, & Thomas, Jonathan P. 2012. Measuring what employers do about entry wages over the business cycle: A new approach. American economic journal: Macroeconomics, 4(4), 36–55.

McDonald, Judith A., & Thornton, Robert J. 2011. Estimating gender wage gaps. The journal of economic education, 42(4), 405–413.

McKay, Sonia, Jefferys, Steve, Paraksevopoulou, Anna, & Keles, Janoj. 2012. Study on precarious work and social rights. Working lives research institute, london metropolitan university.

Melly, Blaise. 2005. Decomposition of differences in distribution using quantile regression. Labour economics, 12(4), 577–590.

Messinis, George. 2013. Returns to education and urban-migrant wage differentials in China: IV quantile treatment effects. China economic review, 26(C), 39–55.

Oaxaca, Ronald. 1973. Male-female wage differentials in urban labor markets. International economic review, 14(3), 693–709.

OECD (ed). 2018a. Oecd emploiment outlook 2018. OECD Publising, Paris.

OECD (ed). 2018b. Oecd emploiment outlook 2018. OECD Publising, Paris.

Onaran, Ozlem, Stockhammer, Engelbert, & Grafl, Lucas. 2011. Financialisation, income distribution and aggregate demand in the usa. Cambridge journal of economics, 35(4), 637–661.

Portnoy, Stephen. 2003. Censored regression quantiles. Journal of the american statistical association, 98(464), 1001–1012.

Powell, David, Baker, Matthew, & Smith, Travis. 2014. Generalized quantile regression in stata. 2014 Stata Conference 12. Stata Users Group.

Ravallion, Martin. 2009. Evaluation in the practice of development. The world bank research observer, 24(1), 29–53.

Rosenbaum, Paul R., & Rubin, Ddonald B. 1983. The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41–55.

Rossi, Peter H., Lipsey, Mark W., & Freeman, Howard E. 2004. Evaluation: A systematic approach. SAGE Publishing.

Rossman, P. 2009 (February). Financialization and casualization of labour – building a trade union and regulatory response. Paper presented at the Global Labour University Conference, Mumbai.

Rothe, Christoph. 2010. Nonparametric estimation of distributional policy effects. Journal of econometrics, 155(1), 56–70.

Rubin, Donald. 1972. Estimating causal effects of treatments in experimental and observational studies. Ets research bulletin series, 1972(2), i–31.

Rubin, Donald B. 2005. Causal inference using potential outcomes. Journal of the american statistical association, 100(469), 322–331.

Santangelo, Giulia. 2011. Do temporary contracts cause wage discrimination? a quantile treatment effect analysis for europe.

Schaefer, Daniel, & Singleton, Carl. 2017. Real Wages and Hours in the Great Recession: Evidence from Firms and their Entry-Level Jobs. Tech. rept.

Stock, James. 1989. Nonparametric policy analysis. Journal of the american statistical association, 84(406), 567–575.

Stockhammer, Engelbert. 2013. Why have wage shares fallen? a panel analysis of the determinants of functional income distribution: for the international labour organisation (ilo) project ”new perspectives on wages and economic growth”. Ilo working papers. International Labour Organization.

Stockhammer, Engelbert, Onaran, Ã–zlem, & Ederer, Stefan. 2008. Functional income distribution and aggregate demand in the Euro area. Cambridge journal of economics, 33(1), 139–159.

UNESCO. 2011. International standard classification of education - isced 2011. Unesco Institute for Statistics.

Wooldridge, Jeffrey. 2007. Inverse probability weighted estimation for general missing data problems. Journal of econometrics, 141(2), 1281–1301.

Xie, Yu. 2011. Causal inference and heterogeneity bias in social science. Inf. knowl. syst. manag., 10(1-4), 279–289.

Xie, Yu, Brand, Jennie E., & Jann, Ben. 2012. Estimating heterogeneous treatment effects with observational data. Sociological methodology, 42(1), 314–347.

Zhu, Rong. 2011. Individual heterogeneity in returns to education in urban china during 1995–2002. Economics letters, 113(1), 84 – 87.