Temporary employment and wage gap with permanent jobs: evidence from quantile regression

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TEMPORARY EMPLOYMENT AND WAGE GAP WITH PERMANENT JOBS: EVIDENCE FROM QUANTILE REGRESSION

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Abstract

Previous research on wage penalty for temporary workers has focused on the conditional mean model. This paper uses micro data from the 2006 wave of the Survey of Italian Households' Income and Wealth (SHIW) to examine the wage gap between temporary and permanent workers across the whole wage distribution. I apply a quantile regression models to understand whether there are glass ceiling or sticky floor for fixed-term workers and to test the hypothesis of polarization of wage profile by contract status. I also exploit a counterfactual decomposition analysis to investigate whether the gap is attributed to differences in characteristics or to differences in coefficients effect.

A possible source of misspecification may arise, the endogenous selection in temporary status. In order to address the selectivity bias, I adopt an IV specification and a variant of the traditional Heckman (1978) dummy endogenous variable for the quantile framework.

The main finding is a sticky floor effect, in the sense that the wage penalty for temporary workers is wider at the bottom of earnings distribution and in particular the decomposition method shows how the coefficients effect is decreasing in the upper half of wage profile. The analysis by educational level and by sector confirms the sticky floor effect. Finally correcting for endogenous self-selection in temporary contract slightly modifies the magnitude of wage gap, without changing the main patterns evidenced in the standard quantile regression.

Keyword: temporary employment, quantile regression, wage gap decomposition, endogenous selection

Introduction

During the last decades, European countries witnessed a significant expansion of temporary employment. The growth of fixed-term contracts has been triggered by the process of liberalization which has contributed to lessen the rigid employment protection legislation and to make more flexible the labour market. The increase of atypical contracts has generated a concern over its effects on labour market equilibrium. In particular the relative situation of temporary workers has played a central role in the numerous studies carried out in the last years on fixed-term jobs and their consequence in term of wages and employment transition.

Furthermore fixed-term contracts expire automatically at the end of the term fixed without any firing cost for the employer and this means that temporary workers suffer a higher risk of unemployment and of income loss. According to the theory of compensating differentials, different working conditions in presence of the same level of competence should correspond to a wage premium for temporary workers to offset the disadvantages. However the empirical evidence shows a wage penalty for temporary jobs and in recent years several studies have investigated on this topic, finding negative earnings differentials for atypical jobs.

This paper aims to investigate the differences between the wage structures of temporary and permanent workers in the Italian labour market. In particular the focus is to analyze the wage gaps across the whole pay distribution to understand whether there are “glass ceilings” and “sticky floors” for fixed-term workers in Italy. The pay gap may be different in the upper and lower tails of earnings distribution. The glass ceiling effect refers to a wider wage gap at the top of distribution, suggesting that temporary in the high-income jobs are paid less than their permanent counterparts. In contrast a sticky floor effect refers to an opposite situation, when the gap widens at the bottom of the wage distribution. I hypothesize a sort of polarization of wage profile by contract status, distinguishing between temporary and stable job, and I try to emphasize the extent to which work duration affects the location and shape of the conditional wage distribution.

A growing number of studies has attempted to analyze the phenomenon and promoted greater understanding of its evolution. I evaluate the presence of a wage penalty for temporary contracts in Italy and whether the wage gap between two groups of workers is due to the distribution of employment contracts in the different type of jobs or whether they present different returns for the same characteristics.

Most of the empirical studies that have investigated the permanent wage premium have looked exclusively at the conditional mean models and considered different ways of addressing the selection issue related to contract type. I use the quantile regression technique to explore the source of heterogeneity in the wage gaps between temporary and permanent workers.

Differently from the standard OLS approach, the quantile regression (hence after QR) framework provides a more flexible method to characterizing the effect of temporary status on different percentiles of the conditional wage distribution, thus enabling to shed further light on the location, scale and shape of the log wage distribution. Another advantage of QR model concerns the coefficient estimates that are more robust to outliers of dependent variable and, in presence of non-normal errors, may be more efficient than OLS estimates (Buchinsky, 1998).

To examine the pay gap across wage profile, one has to go beyond the traditional OLS regression and Blinder-Oaxaca decomposition and to exploit several methods available to decompose the wage differential at each quantile. Thus I perform the Machado–Mata techniques (hence after MM) for QR model to assess the relevance of glass ceiling or sticky floor hypothesis and to investigate the magnitude of difference in earnings between temporary and permanent workers. The MM techniques is applied using the procedure proposed by Melly (2006) to study the differences in distribution in the quantile regression framework. The empirical analysis decomposes the difference between the temporary and permanent log wage distributions into one component based on the difference in labour market characteristics (endowments effect) and one component based on the difference in rewards for the same characteristics (coefficient effect). The idea is to generate a counterfactual temporary log wage density that would arise if fixed-term workers were given permanent's labour market characteristics but continued to be paid like temporary.

Nevertheless a possible source of misspecification may arise in this framework, the potential endogeneity of the temporary status which may bias the QR estimates, given that the role of unobservable individual characteristics cannot be ignored as well as the potential correlation between the temporary dummy variable and the error term in the wage equation. In order to address the issue of endogenous selection in temporary contract, this work examines the empirical implication of allowing the dummy variable for contract type to be correlated with the error term. Thus I adopt an IV method and a variant of the Heckman (1978) dummy endogenous variable model to correct the bias induced by the endogeneity of contract status.

In particular for the IV approach I present a traditional 2SLAD estimator[1] and a Quantile Treatment Effect (QTE) estimation strategy (as Abadie et al., 2002) that allows to look at the impact of temporary status throughout the income distribution.

[1] The 2SLAD estimator has been used in the literature about returns to schooling to correct the endogeneity of education level (see for example Arias et al. 2001; Girma and Kedir, 2005) but the fitted values approach may present some problem whether the treatment effect widely differs across quantile.

Differently the traditional self-selection issue, proposed by Heckman (1978) and present in the empirical studies on wage differentials, has been revised from Buchinsky (1998, 2001) in the QR framework, introducing a two-step in semi-parametric process to correct for the self-selection. In this paper I apply a variant of the Buchinsky approach to account for the selectivity bias in my wage equation.[2]

The dataset used here to explore wage differentials is the 2006 wave of the Survey of Italian Households' Income and Wealth (SHIW), a representative survey carried out by the Bank of Italy. Therefore I focus in my empirical exercise on the sub sample of employees with age between 15 and 65 years that are employed on temporary or permanent basis. In particular I wish to understand whether the temporary jobs evidence a wage penalty with respect to open-end contracts and whether this gap is due to different individual characteristics or to discrimination in the labour market.

Several studies have looked at the pay gap between temporary and permanent workers and in particular for the Italian labour market (Picchio, 2006, 2007; Tanda e Rossetti, 2007) they find the existence of a wage penalty for fixed-term jobs, lower with respect to other countries. But all these studies analyse pay gap at the conditional mean, which may hide significant differences at the bottom or top of the wage distribution. This study complements and adds to the previous research in many ways. Works on how much the temporary status wage penalty varies across the wage distribution have emerged recently and comparing wage not only at the mean is important to correctly capture the presence of segregation or discrimination and to evaluate the impact of individual characteristics at different point of earnings distribution.

In addition I investigate more in depth the link between educational level and wage penalty that should be of great interest especially for policy makers for whom it is crucial to better understand the effects of flexibility in the Italian labour market. My study also complements Picchio (2006), which used the 2002 wave of SHIW to examine the wage differentials between temporary and permanent workers. Picchio (2006) looks at the wage penalty for temporary worker and accounts for self-selectivity bias in contract status dummy applying IV and sample selection models in a conditional mean framework. So this paper also contributes to the literature on the temporary-permanent wage differentials for the Italian labour market, controlling also for endogenous contract type in a QR framework.

The main empirical findings are in favour of the sticky floor hypothesis, in the sense that the wage gap between temporary and permanent workers is wider at the bottom of the distribution,

[2] The selectivity issue in wage gap literature has been widely account in several works. Previous studies has applied a variant of the traditional semi-parametric Bucinsky approach, exploiting several estimator (probit or other semi-parametric model) to calculate the power expansion of inverse Mills ratio in the first step. Different example are Arulampalam et al. (2006) about union wage premia and Melly (2006) and Hyder and Reilly (2005) for public sector pay gap.

while at the top it is not significant. In particular the Machado-Mata decomposition shows how the coefficients effect (a measure of discrimination) is monotonically decreasing after the 30th percentile, especially for women. Moreover the differences in the upper tail of distribution are explained by difference in labour market characteristics, as for example education, experience and occupation. The analysis by educational level and for sector confirms a significant negative coefficient effect for temporary workers in the lower tail of earnings distribution, which may indicate the "port of entry" nature of temporary employment, in particular for young and high-skilled workers. Finally correcting for endogenous self-selection in temporary contract modifies the magnitude of the differentials, without changing the main patterns, as QR regression.

The plan for the paper is as follows. In section 2 I discuss the econometric model and the specification of quantile regression, as well as the decomposition method applied. Section 3 describes the dataset used for the empirical exercise, the rule for sample selection and presents some descriptive statistics. Section 4 reports the empirical findings and the decomposition of wage differential and finally section 5 draws the conclusions.

2) The econometric model

2.1) Quantile regression model

In this section I disentangle the contribution of workers' characteristics and contract type on wage setting process in the Italian labour market. Several contributions have examined the wage gap between temporary and permanent workers using a standard OLS framework[3] and taking a Mincerian standard specification[4] as starting point. It consists on estimating a traditional wage equation, including a dummy variable for temporary contract.

To investigate whether the wage penalty (or premium) varies at different points of earnings profile, I deviate from this practice by looking at the effect of con tract type and other covariates on the whole wage distribution, thus employing a quantile regression model (Koenker and Basset, 1998). In addition, linear regression, as OLS and other standard statistical techniques, focus only on mean effect, emphasizing the impact of each covariate as a

[3] For instance Picchio (2006, 20007), Tanda and Rossetti (2007) for Italy, Jahn (2008) for Germany, De La Rica (2004), Davia and Hernanz (2004) for Spain and Van Der Wiel (2008) for Netherlands.

[4] The specification of the wage equation is an extension of well-known Mincer model of wage determination and it controls for age and its square, work experience (and its square), tenure in the present job (and its square), five education dummies, a dummy for contract type (temporary or permanent), region of residence, demographic characteristics (a marital status dummy and a dummy on whether one is the head of household, firm size dummies, industry dummies and three occupation dummies (white collar, blue collar and manager). Summary statistics are presented in table 1.

simple "location shift" (Melly, 2005). Therefore the quantile regression (QR) is a natural extension of OLS estimation of conditional mean model and it describes the conditional quantile regression as a linear function of observed heterogeneity, providing a detailed description of the conditional wage distribution.

I specify the θ^{th} $(0 < \theta < 1)$ quantile of the log wage distribution (w_i), conditional on a vector of covariates x_i as

$$q_\theta(w_i \mid x_i) = x_i \beta_\theta$$

implying

$$w_i = x_i \beta_\theta + \mu_\theta, \quad \text{with} \quad q_\theta(\mu_\theta \mid x_i) = 0,$$

where μ_θ is the error term of θ^{th} conditional quantile that is assumed to be zero.[5] Moreover QR results are robust to outliers and heavy tailed distributions.

The quantile estimator of β_θ solve the following minimization problem:

$$\hat{\beta}_\theta = \arg\min_\beta \left[\sum_{i:w_i \geq X_i\beta} \theta \left| w_i - X_i\beta \right| + \sum_{i:w_i < X_i\beta} (1-\theta) \left| w_i - X_i\beta \right| \right].$$

The minimization problem can be solved into a GMM framework which has been applied to demonstrate consistency and asymptotic normality of $\hat{\beta}_\theta$ and to define its asymptotic covariance matrix. Thus, I estimate a single equation QR model as

$$w_i = \alpha_\theta temp_i + x_i \beta_\theta + \mu_\theta$$

where $temp_i$ is a dummy indicating contract type and equal to one whether the worker has a fixed-term job and zero if permanent. The set of QR coefficients provides the rates of return to the corresponding characteristics at the selected quantile of the conditional wage distribution. If the impact of temporary contracts is the same across the entire conditional wage distribution, I would expect α_θ not vary for different θ. In addition, the variations in α_θ across different quantiles could reflect heteroscedasticity. Moreover, if heteroscedasticity concerns interaction between temporary contract and unobserved determinants of wages, QR model allows to

[5] This is the only distributional assumption on μ_θ. QR model avoids the restrictive assumption that the error terms are identically distributed at all points of the conditional distribution.

derive how the fixed-term contract effect and unobserved heterogeneity impact on individual outcome across different quantiles.[6]

Finally, the single equation model is based on the assumption that the wage determination process is identical for both permanent and temporary workers, i.e. the returns to individual characteristics are the same in both contract type. In order to test this restriction, I estimate a model interacting each independent variable with the contract type dummy and I investigate whether the interaction terms are significantly and jointly different from zero. The null hypothesis is rejected, thus the above mentioned assumption is violated. In practice the single equation QR model may be misleading and separate wage equation for each group are required.

2.2) Quantile regression decomposition

Once I have estimated the QR coefficients, as in the OLS approach, the differences at selected quantiles of the wage distribution between two groups of workers can be decomposed into one component due to labour market characteristics and one component that is based on differences in rewards. In addition the implementation of quantile decomposition analysis may provide further evidence to understand whether the unobserved heterogeneity is a source in explaining the nature of the existent wage gap.[7] The usual Blinder-Oaxaca methodology is based on the OLS property that the mean wage conditional on the average characteristics of the sample is equal to the unconditional mean wage. Basically the exact decomposition of the average wage gap between both group of workers is due to the validity of this property. Hence incorporating the QR framework in this decomposition techniques based on conditional mean model may be misleading.

Furthermore the unconditional θ^{th} quantile wage is equal to its θ^{th} quantile wage conditional on the vector of explanatory variables at the same quantile plus the average of those individuals' error terms as

$$q_\theta (w_i \mid x_i) = x_i \beta_\theta + \mu_\theta \, .$$

But the error term in QR is not zero, so the exact decomposition of the wage differential (as in Blinder-Oaxaca methodology) cannot be performed at different quantiles.

[6] In order to prove the heteroscedasticity hypothesis, i.e. the case in which slope coefficients are different for the same variables across quantile, I test that the estimated coefficients vectors from different QR are statistically different from one another.

[7] In practice I investigate whether the existence of sticky floor or glass ceiling is due to the prevalence of a composition effect (differences in labour market characteristics, as educational level, experience, occupation) or a price effect (differences in rewards, i.e. whether the rate of return for the same characteristics is different).

More recently, Machado and Mata (2005) have proposed a quantile-based decomposition method, which combines quantile regression with bootstrap approach and it has been addressed in a wide range of empirical studies.[8] This procedure extends the traditional Blinder-Oaxaca decomposition on conditional mean wage to the whole wage distribution by allowing to overcome the above mentioned problem. Assuming linearity[9] between the quantiles of the dependent variable w_i and the covariates X_i, the main methodological contribution of the Machado-Mata (MM) procedure is to derive an estimator of counterfactual unconditional wage distribution.

In this paper I follow Melly (2006) who suggests a modified procedure of MM technique to decompose differences at different quantiles of the unconditional distribution. Instead of randomly drawing θ from an uniform $U(0,1)$, the conditional distribution is estimated by quantile regression for a large number of selected θs, such that $\theta_1,..,\theta_j,..,\theta_J$ (with j = 1,…, J) and then the conditional (log) wage distribution is integrated over the range of the explanatory variables. Let $\hat{\beta} = (\hat{\beta}_{\theta_1},...,\hat{\beta}_{\theta_j},...,\hat{\beta}_{\theta_J})$ be the QR coefficients estimated at J different quantiles, $0 < \theta_J < 1$ (with j= 1,…, J) separately for both temporary and permanent workers. Then, integrating over all observations and over all quantiles, Melly (2006) derives an estimator of the θ^{th} unconditional quantile of (log) wage as follows

$$q(X_i, \beta_\theta, \theta) = \inf\left\{ q : \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{J}(\theta_j - \theta_{j-1})1(x_i\hat{\beta}_{\theta_j} \le q) \ge \theta \right\}$$

where $1(\bullet)$ is the indicator function.

In what follows, using the above estimator for unconditional distribution, Melly (2006) estimates the counterfactual distribution by replacing either the estimated parameters of the distribution of characteristics of permanent workers with those of temporary workers. In addition the difference at each quantile of the unconditional distribution can be separate into one component that calculates the difference in the rewards that the two groups (temporary and permanent workers) receive for their labour market characteristics (coefficients effect) and one

[8] Other decomposition procedures have been provided in the literature in order to disentangle the sources of differences in wage distribution. For instance, the plug-in methods of Juhn et al. (1993), based on parametric regression, or Di Nardo et al. (1996), that exploit sample reweighting to apply a semi parametric model. However numerous empirical studies have mainly focused on the Machado-Mata technique to decompose differences along the whole wage distribution, exploiting quantile regression framework.

[9] This means that the θ^{th} conditional quantile is correctly specified as $q_\theta(w_i \mid x_i) = x_i\beta_\theta \;\; \forall \;\; \theta \in (0,1)$.

component that is based on differences in labour market characteristics between temporary and permanent workers (characteristics effect):

$$q\left(x_i^t, \beta^t, \theta\right) - q\left(x_i^p, \beta^p, \theta\right) = [q_\theta(x^t, \beta_\theta^t) - q_\theta(x^t, \beta_\theta^p)] + [q_\theta(x^t, \beta_\theta^p) - q_\theta(x^p, \beta_\theta^p)]$$

where *t* = temporary, *p* = permanent, the first brackets measure the difference in the rewards that the two groups receive for their labour market characteristics, exploiting the counterfactual distribution, while the second brackets measure the impact of differences in labour market characteristics between fixed-term and permanent workers.[10] Overall, the Melly (2006) decomposition generalizes the traditional Blinder-Oaxaca approach and illustrates how differences in rewards or in labour market characteristics affect the wage gap between the two groups across the entire distribution. However an important disadvantage of this methodology is that, unlike the classic Blinder-Oaxaca, it cannot be used to separate the contribution of each variable, thus I can report only the total endowment and coefficients effect for each selected quantile.

2.3) The Endogeneity issue in contract type

As widely discussed in the literature, standard QR results may be biased due to the endogeneity of contract type. In practice, if the choice of working under a temporary or a permanent contract is not exogenous and the workers do not have the same probability of being hired under each type of contract, a self-selection bias may arise due to the non random distribution of employment contracts. Indeed the role of workers' unobserved characteristics on both wages and contract type selection cannot be ignored and accounting for endogenous selection may be necessary to correct the bias mentioned above.

A further potential source of misspecification derives from a sample selection problem. The information on wages is only observable for wage earners, i.e. for those individuals who decide to participate to the labour market. Moreover, being a wage earner may be a characteristic distributed not randomly across the population and whether the error term of the labour market participation model is correlated with the error term of the wage equation, the QR may yield biased estimates even if the endogeneity of contract type is controlled for, due to a sample selection distortion.

[10] For a more detail description of this decomposition approach see Melly (2006). I use Stata package rqdeco (Melly, 2007), estimating 100 quantile regressions in the first step and then to obtain consistent standard errors I bootstrap the results with 100 replications.

Therefore, to account for the potential endogenous selection in temporary contract, I replicate the analysis, exploiting an IV approach and a self-selection model, and in the next two section I will describe the estimation strategy used to deal with endogeneity issue.

2.3.1) An extension of IV: the Quantile Treatment Effect

Several studies on wage differentials have dealt with the possible non-random selection in temporary contracts and have used different estimation strategy in order to account for the endogeneity bias. In particular an IV approach has been adopted to correct for the endogenous self-selection in the literature for the Italian labour, using different excluded instruments. For instance, as instrument, Tanda and Rossetti (2007) use information on whether the workers enters in the labour market after the Treu reform (so being potentially exposed to temporary contracts) or not, exploiting the timing of change in labour market regulation. Further, Picchio (2006) estimates different IV specifications, using an instruments on the job searching dummy variable and whether the worker has taken sick days or not.[11]

In addition, the issue of endogenous variable is not straightforward in the quantile regression framework and thus to address the self-selection bias, differently by previous literature, I adopt an instrumental variable quantile regression (IVQR) approach that looks at the quantile treatment effect (QTE) of being a temporary worker on wages.

Moreover, to perform the QTE estimator, I decide to follow Picchio (2006) and, as instrument, in this paper I use the on the job searching dummy variable, which is equal to one whether the employee is looking for another work or zero otherwise. The consistency of IV estimator is based on the correlation between the instrument and the endogenous dummy variable (being a temporary worker) and on its exogeneity. The searching dummy variable is supposed to be positively correlated to the contract type indicator, because temporary workers should have a higher incentive to search, giving their higher probability to be laid off at the end of the contract. Furthermore the first stage of a 2SLS estimator confirms that the on the job searching and fixed-term contract are positively correlated, with a positive estimated coefficient, statistically different from zero.[12]

[11] In this case the author provides both an IV and a GMM specifications in the study of wage differentials between temporary and permanent workers. GMM estimation strategy allows to test for the jointly validity of the instruments with the Hansen – Sargan test of over identification, so providing a robustness check on endogeneity of contract type. Moreover, he also discusses the possibility to include, as instrument, information on whether the employee has never paid social security contributions.

[12] An issue much debated in the IV framework is the weakness of the instruments used in the empirical analysis, as discussed in Staiger and Stock (1997). For instance, in this specific case, with one endogenous variable and one excluded instrument, the model fall into the just identified case and thus the validity of the instrument cannot be test.

The extension of instrumental variable methods to the estimation of conditional quantile model is discussed firstly in Amemiya (1982).[13] In practice, the estimation strategy consists in using the fitted values from a first step least squares regression of the endogenous variable on the instruments as covariate in the standard quantile regression at the second step. In literature this model is the so-called fitted value approach (2LAD). But, applying a 2LAD estimator, analogous to a 2SLS one, it will most likely result into biased and underestimated standard errors. Thus, to recover consistent standard errors, an approach may be to bootstrap them in both the first stage and in the second stage regressions.[14] Based on the above model and for a comparison device, in this paper I estimate a 2LAD model where the first stage is a regression of the endogenous variable (temporary contract) on the exogenous ones (including the instrument) with a probit model, while the second stage is a linear quantile regression with the fitted value for temporary status.[15]

However, as suggested in previous studies, the fitted value approach is not consistent whether the treatment effect differs across quantile. Other alternative approaches of IVQR estimator have been discussed in the literature (for a detailed description see Frolich and Melly, 2008; Melly, 2006). The subject of quantile regression with endogenous variables has been investigated by Chernozhukov and Hansen (2005) who provide a model of IVQR in presence of discrete endogenous variable. But, as discussed in the introduction, I adopt a quantile treatment effect (QTE) model, following Abadie, Angrist and Imbens (2002) approach, that allows to look at the impact of contract type throughout the wage distribution, controlling for endogenous self-selection in temporary contract. The comparison of both models shows that Abadie et al. (2002) impose more restrictive conditions on the selection equation but allow for heterogeneity in responses.[16] Therefore I exploit the peculiar feature of QTE approach in order to emphasize the heterogeneous impact of flexible contracts across the wage profile.

Alternatively, as suggested by Picchio (2006), on the job searching could have a direct effect on wages whether, for example, the employer decides to offer an higher wage to avoid that the worker accepts another job. Therefore, in this case, the IV estimator is not consistent. In order to make the Quantile Treatment Effect (QTE) approach more robust, I have also run a further specification in which the instrument used is the dummy variable sick, equal to one if the employee has taken days for sick and zero otherwise, as proved in Picchio (2006). The results are quite similar and the main patterns do not change. Finally, to overcome the possible weakness of the instrument, one could use the lagged incidence of temporary employment by region, skill and sector to control for local availability of temporary job by skill and sector. But, to exploit the QTE estimator proposed by Abadie et al. (2002), I haveto use a binary instrument and so the on the job searching seem to be a quite robust choice.

[13] Amemiya (1982) has considered quantile regression model combined with an endogenous variable, reporting the consistency and asymptotic normality of a 2LAD estimator, but having in mind a conditional median regression (LAD model)

[14] Arias et al. (2001) use the bootstrap approach to obtain consistent standard errors when they investigate return to schooling with instrumental variable quantile regression. A similar framework is udes by Garcia et al. (2001) in a study on gender wage gap applying QR model.

[15] Both stage are calculated using the bootstrap technique with 100 replications.

[16] I mean heterogeneity conditional on X and the quantile of interest, while both estimators allow for different treatment effects at different quantiles (see also Melly, 2006)

Abadie et al. (2002) propose a parametric estimator, based on the local average treatment effect (LATE) model of Imbens and Angrist (1994), which can be applied only to a specific case: a binary endogenous treatment variable D and a binary instrument Z. Abadie et al. (2002) provide conditions under which a Quantile Treatment Effect (QTE) model can be estimated:

1. Independence assumption, i.e. (Y_1, Y_0, D_1, D_0) is jointly independent of Z given X.
2. Non trivial assignment, $0 < P(Z = 1 \mid X) < 1$
3. $E[D_1 \mid X] \neq E[D_0 \mid X]$
4. Monotonicity assumption, i.e. $P(D_1 \geq D_0 \mid X) = 1$

Thus for each θ $(0 < \theta < 1)$ there exist δ_θ and β_θ such that

$$q_\theta(Y \mid X, D, D_1 > D_0) = \delta_\theta D + X^{'}\beta_\theta ,$$

where $q_\theta(Y \mid X, D, D_1 > D_0)$ denote the θ-quantile of Y given X and D for compliers. Under these conditions, I can compute a consistent estimator of δ_θ and β_θ.

The four conditions described above are derived from Angrist and Imbens (1994) in order to recover the local average treatment effect (LATE) interpretation of 2SLS.[17]

Under these assumptions, Abadie et al. (2002) identify the marginal distribution of the potential outcomes for the sub-population of compliers and they suggest that the conditional quantile treatment effect can be estimated as a weighted quantile regression:

$$(\hat{\beta}_{IV}, \hat{\delta}_{IV}) = \arg\min_{\beta,\delta} \sum W_i^{AAI} . \rho_\tau (Y_i - X_i\beta - D_i\delta)$$

where $W_i^{AAI} = 1 - \frac{D_i(1 - Z_i)}{1 - \Pr(Z = 1 \mid X_i)} - \frac{(1 - D_i)Z_i}{\Pr(Z = 1 \mid X_i)}$.[18]

More generally, the QTE approach captures the impact of an intervention on the whole distribution for individuals whose treatment status is changed by a binary instrument.[19]

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[17] In this framework, the first assumption implies that searching for another job is randomly assigned. In practice I cannot test this assumption, but I find that temporary workers are not significantly different from each other whether they search for another job or not. The third condition simply requires a significant first stage, as I explained in this section. The fourth condition basically implies that there not exists workers for whom searching another job reduces the probability to be temporary. In addition the model requires the presence of compliers and the treatments effects can be identified only for this group.

[18] A preliminary estimator for $\Pr(z = 1 \mid x_i)$ is necessary to implement QTE approach, but some of the weights may be negative. Moreover, Abadie et al. (2002) use a series estimator, while the Stata package IVQTE used in the estimation procedure, applies a local estimator, setting to zero the estimated weight that are negative in finite samples.

[19] Finally, I exploit bootstrap technique with 100 replication in order to obtain robust standard errors.

2.3.2) Self-selection approach: an extension of Dummy Endogenous Variable Model

To guarantee the robustness of QR estimates, I need to account for a potential self-selection bias. Indeed if I do not correct for endogenous selection, usual QR risks yielding biased estimates, given that the disturbance term and the independent variables in the wage equation could be correlated. Either through a self-selection by workers or sample selection by employers, the location of individuals in either contract type may not be considered as the result of a random process.

For the QR model, I control for endogenous selection by applying a variant of the standard Heckman two-step procedure (1978), as it was introduced by Buchinsky (1998, 2001) and based on a non parametric method. There is currently little consensus regarding the most appropriate correction procedure for selectivity bias in QR model, also exploiting a higher order series expansion, based on the inverse Mills' ratio.

Nevertheless this approach presents some complications that arise in regard to identifying the constant term in such wage regression models when higher order terms are used to capture selection bias. To get unbiased estimates of β_θ, it is necessary to introduce an extra term in the quantile wage equation to correct for selectivity as evidenced:

$$q_\theta(w_i \mid x = x_i) = x_i^{'}\beta_\theta + h_\theta(g) + \varepsilon_\theta$$

where

$$h_\theta(g) \equiv q_\theta(u_\theta \mid x_i, g > 0)$$

such that $q_\theta(\varepsilon_i \mid x_i, g > 0) = 0$.

Following the two-step Buchinsky approach, the $h_\theta(g)$ is approximated by a power series whose coefficients has to be estimated and should define a function which is larger when the impact of unobservable is larger. This function is the inverse Mill's ratio, being small for those with an high probability of being temporary and increasing monotonically as the probability of being temporary reduces. As exclusion variable in the first step, I adopt on the job searching dummy variable.[20] Hence I control for the selectivity bias in QR wage equation expanding $h_\theta(g)$ as a power series in the inverse Mill's ratio.

In the first step I have to estimate the probability of workers being in temporary or permanent contract. The traditional method in the selection step uses a semi-parametric least square which

[20] Whether I suppose that there not exist exogenous variables which account for the selection into temporary contracts and which are excluded from the wage equation, the identification of the self-selection model derive from a distributional assumption, i.e. the non linearity of the correction term (hazard term).

makes no assumptions about the distribution of the residuals. However a different strategy is followed in this paper, where I apply two ordinary probit selection equations (distinguishing by region, i.e. North vs. Centre-South) similarly to Heckman (1979) and from there derive the bias correcting factor (i.e. the inverse Mill's ratio), as in Arumpalam et al. (2006). In the second step, a linear quantile regression is performed by additionally including the derived correcting factor. The $h_{\theta}(g)$ function is approximated by the inverse Mill's ratio and its square. A different model specification with a series of power 3 (of Mill's ratio) is tested and the result is similar.

3) Dataset and descriptive statistics

The empirical analysis has been carried out also on the 2006 wave of the Survey of Italian Households' Income and Wealth (Shiw), a nationally representative survey conducted every two years since 1989 from the Bank of Italy. It covers 7,768 households composed of 19,951 individuals and 13,009 income-earners, providing information about individual and job characteristics, contract type (temporary, interim and permanent work), the average monthly wage and the hour worked. The 2006 wave of SHIW dataset covers 7,236 employed workers of which 5,808 employees and 1,424 self-employed workers.

To investigate the impact of temporary contracts on wages, I select the sub-sample of employed workers but removing the self-employed worker since their earnings are driven from more complex factors, as taxation, and they are structurally different from employees. Then I excluded observation lying in the first and in the last percentiles of the weekly working hours and yearly earnings respectively. Further I consider only individual with a working age between 15 and 65 years, excluding observations which have missing values for some covariates.

The main variable is the type of contract $temp_i$, a dummy variable equal to one whether the individual is fixed-term or interim worker and equal to 0 if the individual has an open-end contract. The dependent variable is the logarithm of the average hourly wage, defined combining the information provided by the SHIW on the yearly earnings and average working hours. In particular employees are asked to specify how many months they are worked during the year and in the same way the average weekly working hours including overtime. Differently fringe benefits are removed from total earned income, which is net of taxes and social security contribution. Exploiting this information I can compute the logarithm of net hourly wage for all employees in the sample, both temporary and permanent.

In order to draw a picture of temporary work and wage gap in Italy, I present some descriptive statistics, computed using the 2006 wave of SHIW. Table 1 shows the profile of employees, distinguishing then between temporary and permanent workers. Employment, permanent one in particular, follows a stronger "gender pattern". Further the level of education is higher on average for permanent workers with more than 51% that have at least an high school qualification while for temporary the same percentage is around 47%.
Regarding the age profile, fixed-term jobs are diffused among the youths, with more than 70% of temporary workers having less than 40 years. Differently the open-end works are concentrated among the adults where more than 50% is older than 40 years. This clearly illustrates the strategy of flexibility at the margin, with an higher diffusion of temporality rate among the weaker categories, as young workers, women and immigrants.
From a macro-region analysis, table 1 reveals how in the Southern there are the 44% of temporary workers, while only 24% of permanent ones, so confirming the dual structure of Italian labour market. Moreover the 55% of permanent workers are resident in the North.
Then the distribution of workers among occupations is related to one of the skill levels: high qualified worker (manager) and white collar tend to register lower temporality than unskilled workers and blue collars. And last but not least fixed-term employment is quite unequally spread across sectors and different firm size. Thus it common in building and in agriculture and it is likewise used by small and medium firm up to 50 employees. On the opposite extreme public services and industry and mining are the ones that register the highest portion of permanent position, together with large firm, higher than 50 employees.
Table 2 displays a picture of the unconditional wage dispersion for temporary and permanent workers at various percentiles of the distribution (10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th} and median). I also show a measure of the wage dispersion, the 0.9-0.1 spread for both contractual status. The unconditional log hourly wage evidences a wider gap at the bottom of distribution, which decreases as I consider the upper tail of distribution. Moreover the spread 0.9-0.1 is higher for temporary than for permanent workers. Hence the data suggests the presence of a "glass floor" hypothesis, exhibiting a stronger wage differential between temporary and permanent at the lower percentile of distribution.
The figure 1a and 1b provide a visual summary of the temporary and permanent wage distribution and the density functions were estimated using an Epanechinov kernel estimator. It can be seen from these figures that the distributions are quite distinct between contractual types. The permanent earnings distribution is characterized by a higher density function around the mode and a lower dispersion with respect to temporary distribution. But to control for the

effects of differences in the distribution of worker characteristics between contract type, I look at the quantile regression model in the next section.

4) The empirical results

Labour market literature on wage differentials has recently discovered the importance of controlling for the difference in pay gap along the whole distributions, given that wide differentials may arise at the bottom or at the top of distribution (for example see Melly, 2006; Arulampalam et al. 2006). In the quantile regression analysis two main effects may be identified. A "glass ceiling" effect is identified, in this study, when temporary workers, who are otherwise similar to permanent ones, tend to fall behind permanent at the top of wage distribution, while a "sticky floors" phenomenon is identified when the gap between temporary and permanent workers widens at the bottom of distribution. In the next paragraphs I present the quantile estimates with and without sample selection and the wage gap decomposition, applying the Machado-Mata techniques.

4.1.) Quantile regression

In this section I present the results for the econometric model outlined in section 3 to investigate whether the relationship between hourly wage and individual characteristics differ between temporary and permanent workers along the different quantiles of the whole wage distribution. According to the descriptive statistics presented in table 1-3, the discrepancy between the permanent and temporary log wage could be in part derived from differences in permanent's and temporary's labour market characteristics as for example age, education, occupation and industry. Thus in table 4 I further investigate the wage gap evolution between permanent and temporary workers throughout the wage distribution and I present the quantile regression respectively for the 10th, 25th, 50th, 75th and 90th quantile, controlling for individual and firms characteristics. Due to limited number of temporary in my sample, I believe that the comparison could be flawed at the bottom or at the top of the wage distribution.
Furthermore the coefficient of contractual type dummy may be considered as a measure of the impact of temporary status on the wage profile for each worker, a sort of raw index of labour market discrimination against temporary workers. My results are in favour of the "sticky floor" hypothesis for atypical workers, in the sense that the wage gap is wider at the bottom of the distribution, as evidenced in table 4.

At the bottom of the distribution (10^{th} percentile), the gap is about 20,6% and it is statistically significant at the 1%. Then the temporary-permanent wage differentials is lower at the 25^{th} and 50^{th} percentile, around 13,3% and 11,3% and always statistically significant at the 1%. A further reduction is present at the 75^{th} percentile where the gap is now slightly more than 6% and significant at the conventional level. Finally the data shows a marked reduction in the wage differentials at the upper tail of distribution (90^{th} percentile) where the sign is reverse and the coefficient is now positive, around 3,3% but not statistically significant. These results reject the hypothesis of "glass ceiling" which prevents temporary from reaching high wages, suggesting that the link between flexibility and wage gap could be a problem for weaker workers at the bottom of the distribution.

Figure 2 reports the coefficient estimates and their 95 per cent confidence intervals for the temporary dummy, comparing quantile regression and OLS models by gender.[21] Comparing the estimates from quantile and OLS regression, it notes that for both females and males the OLS coefficient tends to underestimate the wage penalty for temporary workers until the 60^{th} percentile. In particular the difference between OLS and quantile estimates appear more wider at the bottom and top ends of the conditional wage distribution both for male and female workers.

To confirm this feature and to shed further light on the nature of wage gap, I look at the effect of explanatory variables on log hourly wage across the whole distribution, to find a theoretical explanation to the glass floor hypothesis. As I carry out different quantile regression on the combined temporary and permanent dataset, the *temp* dummy coefficient can be simply interpreted as a measure of the extent to which wage gap between the two groups of workers remains unexplained at each quantiles after controlling for individual and job characteristics.

The effect of age is not clear cut across various quantiles, with a positive value around 1% at the 25^{th} percentile and statistically significant at 10% and the opposite sign at the 75^{th} percentiles, while for other percentiles the coefficient is not statistically significant. Differently the impact of experience is increasing and slightly positive in column 1-4, but stronger at the top of the distribution and characterized by decreasing marginal rate of return, given the negative sign on experience squared. A similar but less marked picture is for tenure.

Looking at the education and taking the elementary or none as base category, in column (1) I observe a positive and statistically significant for all four coefficient, with a larger value for university degree, around 23% that in column (5) at the 90^{th} percentiles is more than double,

[21] These graph are obtained using Stata and the grqreg module due to Azevedo (2004) that graphs the coefficients from quantile regression and the standard errors are calculated via bootstrapping with 50 replications. Further it graphs the coefficient and confidence interval from an OLS regression on the same model. For quantile regression the estimates are calculated at each 0,01 percentile point, as well as for the confidence intervals. The OLS estimates are represented through the horizontal line and specific upper and lower 95% confidence interval in the figure 2.

47,7% and always statistically significant at 1%. A similar but lower trend is for other level of education in the different percentiles examined.

The analysis for macro-regions reveals some interesting patterns: considering the North-East as reference category, at the bottom of distribution to stay in the North-West and in the Centre has a slightly negative effect on log hourly wage. Differently to live in Southern has a stronger negative impact. The estimates for the 25th percentile report a penalty around 3% for the North-West and 14% for the South, both statistically significant at 1%. The pattern changes at the top of distribution, in particular looking at the 75th percentile the difference between the North-West and the South is now narrower, probably because for the high-wage jobs the penalty of living in the South is lower.

In addition, the firm size dummy variables show an increasing wage rate with the number of employees that is stronger at the bottom than at the top of wage distribution. For example to be employed in a firm with more than 500 employees increases the wage of 24% at the 10th percentile and of 19% at the 90th percentile, using always as reference category firm up to 4 employees. The effects are all statistically significant at the conventional level. Furthermore the public firms positively affect the wage in particular at the bottom of distribution, as shown in column (1) at 10th percentile, with an effect around 28% and statistically significant. This impact tends to be lower at the top of the distribution, as for example in column (5) at the 90th percentile (around 19%). A possible explanation is that public sector has a more compressed wage distribution and the public sector wage premium could be highest at the lower end of the wage distribution and then to decrease monotonically, as found for other countries.

A reverse pattern is shown whether I look at the manager dummy which effect is instead monotonically increasing along the whole distribution with a larger spread from the 10th to the 90th percentile (18% vs. 27%). At last the gender dummy seem to indicate the presence of a constant gap between male and female around 9-10%, always significant and similar in almost percentiles estimates.

To exploit the gender differences, I replicate the model for both male and female and in table 5 and 6, I report the quantile regression for men and female separately.

Table 5 shows the estimates for female, exhibiting the same pattern as the above model for all sample, but some important dissimilarities between female and male appears, for instance in the magnitude of coefficients. As mentioned previously, the temporary status has a lower negative impact for female workers. Indeed at the 10th the gap is around 14% and statistically significant at 1% and this pattern is confirmed until 50th percentile where the coefficient is -0.082 (about 8%), so accepting the glass floor hypothesis. But these estimates evidence how the penalty for temporary status has also a gender dimension that favours female. Nevertheless at the top of distribution the coefficient is positive and not statistically significant, in line with the previous results.

A further observation is about regional dimension. Here at the bottom of distribution (10th and 25th) to stay in the Southern has a greater negative impact on wage rate, respectively 33% and 17%, while the coefficients for other regions is similar to previous table. Finally, as outlined above, the public sector strengthened the positive effect for female workers (31% at the bottom of distribution), probably due to its more compressed wage structure.

Table 6 presents the estimates for male workers. First, the gap between temporary and permanent is higher, in particular at the bottom of distribution, but the pattern is well-defined and reverse only at the 90th percentiles. For example at the 10th percentile the penalty is around 23% and statistically significant at 1%, ten percentage points of difference with the same percentile for female workers. The 75th percentile shows yet a significant penalty for temporary workers about 10%, albeit a substantial reduction. Hence the wage differentials are wider for male worker and in part present also at the top of distribution.

As expected to be a manager has a stronger impact than for female workers, in line with the literature on female employment segregation that outlined a poor presence of women in high-level job position. Married status also positively acts on wage rate, around 5-6% on the whole distribution while the rate of return of experience is statistically significant only in the upper tail of distribution, with a return around 1%. The pattern for education, firm size and region of residence is similar to previous estimates.

4.2) Machado-Mata decomposition and wage gap: coefficient or characteristics effect?

Table 9 presents the results from decomposing the earning gap between temporary and permanent workers for selected percentile, using the Melly (2006) estimator applied to quantile regression. Here the interest is the decomposition of wage gap in an endowment and coefficients effect, to account for the presence of discrimination in the Italian labour market, looking before to all sample and then replicated for male and female separately.

The Machado-Mata decomposition using the quantile regression and the Melly (2006) estimator shows that the part due to difference in characteristics and the part due to the coefficient effect vary throughout different percentile. Looking at the column (1) of table 7, for the 10th and 20th percentile, the raw difference between permanent and temporary is high, around 30% but the hypothesis of glass floor for temporary seem to be confirmed, as evidenced by the negative coefficients effect that accounts for about half of total raw differences. Although this evidence, still significant appears the difference in labour market characteristics, constant in all selected percentile (around -0.160). As evidenced in previous estimates, the upper tail of distribution (from 60th percentile) shows a monotonically reduction of the coefficients effect, that combines with the endowments effect clearly suggests a progressive reduction of discrimination for temporary in the high-wage job.

Column (2) and (3) of table 9 report some interesting feature. For example, the raw differential is higher for female at the lower percentile, but this pattern is reversed approximately at the 40th percentile and subsequently the raw wage gap is higher for male, in particular at the upper tail of distribution, from 60th percentile. Furthermore the component due to differences in return (coefficients effect) is continuously decreasing in absolute term for female, while the pattern is not clear cut for male, especially in the highest percentile.

At the same way the component due to relative endowment tends to be monotonically increasing for female from the 30th percentile, slightly different from the constant trend in male column. For the 80th and 90th percentile of women distribution, essentially the entire gap is accounted by differences in endowments effect between temporary and permanent, as the coefficient effect is near to zero.

Column (4)-(6) repeat the same decomposition techniques but controlling for sample selection, as described in the section about econometric model. The table 9 show that the introduction of polynomials in inverse Mill's ratio reduces the proportion of wage penalty explained by the coefficient effect without modifying the main findings.

Thus the general conclusion does not change whichever model used (with or without sample selection term) and supports the proposition that temporary workers are more discriminated at the bottom of the wage distribution and as we move up across quantiles, this effect reduces, in particular for female whose coefficient effect is near zero (or sometimes over) at the top of distribution.

The utility of the results derived from using quantile regression rather than OLS is that they reveal a more complete picture of wage differential between permanent and fixed-term workers and the pay structure of labour market.

4.2.1) Decomposition of the wage gap by individual and job characteristics

Wage gap may vary across educational levels and hence I decompose the wage differential between temporary and permanent workers separately for three ranges of schooling: elementary and middle school, professional and high school and finally university or post graduate degree. Thus figure 3 reports the Machado-Mata decomposition (coefficient effect) separately for the three range of education. The other regressors and the number of replications are the same as in the previous section.

Figure 3a provides the information for university degree. Quantile distribution decomposition shows how the price differential declines as I move up the wage distribution . In particular the wage penalty for temporary is higher for low-wage job at extreme lower quantiles, probably reflecting the port of entry nature of fixed-term employment, used as screening and training instrument. So at the bottom of distribution, the discrimination effect is more significative, then the price differential reduces at the top of distribution, with a confidence interval that includes zero.

A similar picture is confirmed in the figure 3b, which illustrates the coefficient effect for the high and professional school level. The price differential tends to decrease monotonically moving up along the wage distribution. Quite surprisingly at the extreme higher quantiles I observe a sort of wage premium for temporary workers in this educational group, more defined that in university degree. Figure 3c reports the coefficient effect for lower (middle and elementary school) educational group, showing a flat line around zero for almost all quantiles. So the possible wage gap between temporary and permanent for this schooling range seem to be better explained by the characteristics effect, while the figure evidences the absence of a significant discrimination effect.

Concerning the change in the contribution of schooling level to the quantiles of wage equation, the results suggest that educational choices have a different impact on individual wage profile and represent a source of overall wage dispersion in Italy

Then figure 4 shows the counterfactual quantile decomposition using Melly’s approach for the young workers (16-35 years) and captures the heterogeneity in temporary wage penalty along the different quantiles. The characteristics effect seem to be stable over the whole distribution, while the estimated negative coefficients effect varies strongly with different quantiles, showing a monotonic reduction as I go from the lowest to the highest quantiles. The pattern confirms the findings for the high schooling level workers.

The sticky floor effect for fixed-term jobs at the bottom of the wage distribution indicates a sort of discrimination for temporary workers, which in the low-wage works has been exploited by the employers to reduce labour cost and to a screening device. Moving on the wage distribution the earning penalty seems to disappear and in particular at the top of distribution the temporary status is associated with a positive coefficient effect, probably due to the taxation model applied in the Italian labour market.

Figure 5 and 6 report the same decomposition techniques for the North and the Centre-South separately. Therefore looking at the North the total differential is mainly defined by the coefficients effect which indicate a stronger wage inequality than in the South with an higher discrimination at the bottom of distribution that tends to reduce until 20th quantile. Quite differently if I look at the top end of the earning distribution the coefficients effect revenges its sign, assuming positive value. Less volatile is the picture that come from figure 6 for the South, where from the 50th quantile the negative characteristics effect tends to increase so counterbalancing the reduction in discrimination effect for the extreme higher quantiles.
The same empirical exercise is applied to private and public sector (see figure 7-8), revealing a similar picture with a wider variation in earnings differentials in public than private sector. This result confirms recent studies that report an increase of wage inequality in the Italian public sector.
Finally, the wage gap can be decomposed as usual into the discriminatory (coefficients) and non-discriminatory (rewards) components. In the case of differences between fixed-term and permanent wage schedules in Italy, I show that this approach evidences not only different absolute wage differentials according to the location of the worker in the distribution of wages, but also that the contributes of coefficients effect between the two groups modifies along such location. Moreover the pattern of unequal pay gaps in term both of their absolute size and of discrimination effect tends to reduce over the wage scale.

4.3) Selectivity bias in quantile regression

The single wage equation with a dummy variable for contract status must be interpreted with attention because it rely on the strong assumption that the wage determination process is the same for both temporary and permanent workers. This restriction may be violated whether the returns to individual characteristics, as education or job experience, are affected by the contract status, so conducting to a misspecification of the model.
In order to control for, I correct my wage equation for the selectivity bias, applying a variant of the two-step methods proposed by Buchinsky (2001) in the quantile regression framework. Thus I estimate the probability of being a temporary worker conditionally on the other covariates and instrument to describe the selection process and to identify the Mills ratio series necessary as correction term in the quantile wage equation. The estimation is performed by a probit model which relies on the normality assumption for the residuals and distinguishs by

region (North vs. Centre-South).[22] The estimation procedure has also controlled for a gender dimension of selection process in temporary employment.

In the second step, quantile regressions for log hourly wage are estimated, including the inverse Mill's ratio polynomials, based on the probit model results.[23] The selectivity correction terms are not significant with some exception for male workers, in particular at the 25th, 75th and 90th quantiles of the conditional earnings distribution, on the linear λ coefficient. The negative and significant impact of selection term shows that temporary workers earn less than would be expected for their observable characteristics and the phenomenon is observed throughout whole distribution. One possible explanation for such result is that fixed-term workers may be reluctant to bargain aggressively, either due to the temporary nature of their job positions or to the lack of information about what permanent workers with similar observable characteristics are paid.

Table 7 and 8 report the same QR wage equation but controlling for selectivity bias. As a comparison, the selectivity issue has not modified the estimates for female workers, evidencing only a slightly reduction of sticky floor effect for the lower quantile, as well as a not significant wage premium at the top end of distribution. Quite different is the picture that appears for male. Indeed the selection correction term has reduced the wage penalty associated with temporary status across the whole earning distribution, so suggesting that contract status is a more important issue for male workers without modifying the general pattern as outlined in previous sub-section.

4.4) The endogeneity of temporary: the IV quantile regression estimates

It is anticipated that the IVQR analysis correcting for endogenous selection will have slightly different results based on the heterogeneous effect of the temporary work treatment across the entire population. Moreover, the robustness of the model should also give an indication whether the IV assumptions and the validity of the instrument hold in predicting wage gaps for fixed-term workers.

[22] In the traditional Buchinsky model (1998) the first step was performed using a semi-parametric regression which make no assumptions about the distribution of the residuals.

[23] The inverse Mill's ratio polynomials are of second order, $\lambda + \lambda^2$ and are applied separately for male and female. Then the first step probit specification already distinguishes by region of residence, respectively North and Centre-South, to take into account the duality of Italian labour market and the different probability to have a fixed-term contract.

Table 9 reports the 2LAD and QTE estimates for both female and male workers., using as instrument the on the job searching dummy variable.[24] Whether I focus on the 2LAD results for the contract type indicator, I detect that the wage differentials between fixed-term and permanent workers is lower than in standard QR, mainly at the bottom of wage profile.

In addition, the pattern of differences with the standard model seems to suggest that QR models are biased upwards due to endogenous self-selection in temporary contracts for the low-wage job, while no significant differences are found at the top of distribution. The two stage LAD estimates for male workers are lower than the QR counterpart up to the conditional median regression, while the results show a greater wage penalty (than the standard QR) in the upper tail of earnings profile. This suggests the possible presence of a glass ceiling effect for male temporary workers, given that the wage penalty seem to widen for 75th and 90th quantile. However it should be noted that the pattern of the 2LAD estimates is more compressed than the standard QR model, with a similar negative coefficient between the 10th and the 90th quantile for male. But the loss of precision is big enough to render some coefficients not significant in the case of women and thus emphasizing that the 2LAD model fails to represent accurately the pattern of differences in temporary wage penalty encountered along the distribution. Therefore the precision of these estimates is not very high so the implications we are about to discuss do not have a conclusive nature.

For this reason, I focus on the Quantile Treatment Effect (QTE) results that, correcting for the endogeneity, allows to capture the heterogeneous impact of temporary contract throughout the whole distribution. The most remarkable aspect of these findings is how large the relative gap is, accounting for the endogenous selection in temporary contract and using as instrument the on the job searching dummy variable. In table 9, I report for both female and male sample two different IVQR specifications, one controlling only for individuals characteristics and one for both individuals and occupational variable.

At a first look, comparing the estimates from QTE with those from standard QR, it appears that standard quantile regression for female tends mainly to underestimate the wage penalty for female temporary workers across the entire earnings distribution. Differently, the QTE estimates at the bottom of distribution (10th quantile) are lower than the QR counterparts for male workers, while they are higher as I move up along the wage profile. In particular the estimated coefficient is -0.218 at the 10th quantile (vs. -0.233 for QR), therefore controlling for

[24] As above mentioned in a previous section, empirical studies has widely focused on the weakness of instrument to correct the endogenous self-selection in the wage differentials analysis. In practice, I am aware that the validity of the on the job searching dummy as instrument cannot be tested. In order to apply a robustness check, I run different specification to test the validity of my results. In particular I use the days for sick as further instrument and the results do not change. To exploit peculiar feature of QTE estimator I cannot use the lagged share of temporary employment by region, skills and sector to control for a demand side factor. Thus, following Picchio (2006) I report the results for on the job searching dummy variable in a IVQR framework.

the endogeneity of the fixed-term dummy variable reduces the wage penalty for low-wage job. Negative and significant signs are reported for man at almost all quantile of the wage distribution. In practice the wage penalty for male temporary workers is greater in IVQR than in standard QR at the top of distribution (for instance at the 75th quantile -0.151 vs. -0.102).

Furthermore I test for the difference between the QR and QTE coefficients and mainly for women, I'm able to reject the equality between the two model. However, as argued by Autor et al. (2006) for the U.S. labour market, the results show a polarization in the Italian labour market, with higher wage inequality in the lower tail of wage profile and the importance to look not only to conditional mean but across the whole earnings distribution in order to better account for the effect of flexible contracts in shaping wage inequality pattern. In this sense QTE approach allows to describe the heterogeneous impact of temporary contract and showing wider differences along all quantiles than standard QR not accounting for the endogeneity issue.

Moreover if I look at the QTE estimates without controlling for job-related characteristics, I find interesting gender differences on the evolution of the wage penalty along the distributions. In particular the female QTE estimates shows how the wage gap between temporary and permanent workers reduces controlling for occupational variable. It could be argued, as discussed in the gender wage gap literature, that these findings are in favour of the sticky doors hypothesis. This means that the job-related characteristics may account for a wide share of overall wage penalty, indicating how not controlling for the occupational variables could overestimate the real wage gap for female fixed-term workers. Differently the inclusion of occupational variables does not modify so much the temporary coefficient for male workers, who show significant and negative coefficients in both specifications until the 90th quantile.

Finally these results can be compared to estimates from the international literature on wage differentials between temporary and stable workers in order to examine how the wage gap varies after controlling for occupational characteristics. For instance, Graaf-Zijl (2005) found that in Netherlands the raw wage gap is 23 percent and exploiting matching technique, they explain 77 percent of the wage gap with controls for firms size, industry, occupational and wage bargaining information. De La Rica (2004) for Spanish labour market provided a decomposition for the raw wage gap and showed how 42 percent of the gap is due to firm segregation, 9 percent to occupational segregation and 57 percent due to individual characteristics. Differently, Davia and Hernanz (2004) always for Spain found that the wage differentials between temporary and permanent workers are mainly explained by differences in personal and job characteristics, while differences in rewards are not significant.[25]

Thus the main finding in IVQR estimates is that the wage penalty is higher than the one deriving from the standard QR model and therefore if I do not take into account the endogeneity of contract type, I underestimate the wage gap between temporary and permanent workers. Moreover, this result may be interpreted as a positive correlation between the unobservable individual characteristics (like ability) and the probability of holding a fixed-term work, i.e. more able workers choose temporary jobs and lower wages, anticipating that the contract will be renewed with higher wage. In addition, empirical evidence confirms the sticky floor hypothesis, with a wider wage gap at the bottom of distribution, in particular for male workers and the sticky doors effect for women, i.e. controlling for occupational variable is able to explain a large share of the wage penalty.

Furthermore, whether I do not control for sample selection bias,[26] the wage equation estimates may be inconsistent even if I have corrected for the endogenous selection. Thus I carry out the sample selection correction, estimating firstly the latent index model that indicates the participation decision throough a standard probit model. Then I derive a specific Mills' ratio as suggested by Heckman (1979) and Buchinsky (1998). As excluded instruments in this stage I use the presence of children. The probit selection equation includes traditional variables that may act on the participation in the labour market. Further having a children does not directly modify the wage, i.e. it has been argued that there is no correlation between unobservable variables and the probability to have a children.

Moreover, I use the estimated Mills' ratio as the argument in the power series expansion to control for sample selection bias in the QR wage equation controlling for the endogeneity of temporary contract. The results indicate that the correction term are not statistically significant and different from zero (looking at t-statistics for the power series expansion), thus the sample selection bias is not an issue, in line with the literature. I therefore decide not to report the estimates controlling for sample selection bias.

Finally, table 10 summarizes the results on the wage penalty, looking at the coefficient for temporary contract variable. First of all, as robustness check, I perform a second specification of the self-selection model where the identification is obtained only through the non-linearity of the Mills' ratio, without any excluded instrument in the first stage. The results are in line

[25] Further their results indicated that the employment structure of the labour market has played an important role in explaining the wage differentials between temporary and permanent workers, but the presence of a significant selection bias term in the decomposition analysis confirms that indefinite and fixed-term jobs may be quite different.

[26] As above mentioned, the sample selection bias may occur because the sample of observed wages is not randomly selected from the population and thus the decision to participate may be correlated with the error term of the wage equation, making the estimates inconsistent.

with QR estimates and for male workers more similar to QTE approach. In practice, the difference between the QTE estimator and the variant of traditional endogenous dummy variable model may be interpreted as a signal of the failure of self-selection model to capture the heterogeneous impact of temporary contract across the whole distribution, once controlled for the endogeniety. However all three model confirms the presence of a sticky floor effect in the Italian labour market, i.e. the wage penalty for fixed-term works widens at the bottom of distribution.

5) Conclusion

In this work I investigate the existence of wage differentials between temporary and permanent workers in Italy using the 2006 wave of SHIW. In addition, I examine how the wage gap differs along the wage distribution applying a quantile regression model, in the line of several and recent studies for other European countries. Secondly I extend the traditional Oaxaca-Blinder decomposition to disentangle the endowments and coefficients effects in the explanation of wage differentials and to evaluate the presence of discrimination in the rate of return for atypical contracts. In this sense the Machado-Mata decomposition has been performed, using Melly (2006) approach, to provide new insights into the nature and the sources of wage gap in the Italian labour market.

The unconditional wage gap between temporary and permanent is wider at the bottom of the distribution (around 30%) and then tends to decrease monotonically in the top of distribution. In particular the contractual status shows a gap that is far from being constant within the wage distribution. The quantile regression presents the same pattern, confirming the sticky floor hypothesis, with well defined wage differentials for the low percentile of the distribution. Furthermore the gender analysis reports a stronger gap for male worker and a higher spread between the upper and the lower tail of the wage distribution.

Moreover my decomposition throughout the whole wage distribution detects the presence of a wide coefficients effect at the bottom of the distribution which can be interpreted as a sort of discrimination in low-wage jobs for fixed-term workers. For female, after the 30^{th} percentile, the coefficients effects is monotonically decreasing and so in the upper tail of distribution the difference in earnings appear to be the consequence of different labour market characteristics. Quite different is for male, where the rate of return effect seems to be present also at the top of distribution. In addition, the pattern of unequal gaps between temporary and permanent wages is such that both their absolute size and the portion that can be attributed to differences in reward (discrimination) reduces over the pay scale. This pattern could provide an explanation to the lack of a robust relationship between OLS measures of wage gap and the perceived wage discrimination.

Wage gap may vary across educational levels or by sector and hence I replicate the Machado-Mata decomposition on different sub-sample to investigate whether the discrimination effect is distributed equally between categories or whether it regards only some disadvantaged groups. The analysis for schooling range confirms that for high-skilled workers the coefficient effect is negative and suggests the presence of a wide wage penalty that tends to reduce as we move along the distribution and at the top of earnings profile we observe also a revenge in sign with a positive (or near to zero) discrimination effect for fixed-term workers. Similar results appear whether I compare public and private sector.

As suggested in literature I also control for possible source of misspecification in wage equation and tries to correct for the self-selection (or endogeneity) in temporary contract and for sample selection, applying firstly a variant of Buchinsky methods (2001) and then the IV estimates, comparing different approach. The results are not completely clear-cut but seem to confirm the presence of a sticky-floor effects and to indicate that the endogeneity bias is significant, mainly at the bottom of the wage distribution.

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Tab.1: Distribution of permanent and temporary work by personal and job characteristics in Italy, 2006

	All sample	Permanent	Temporary
Men	57,4	58,0	53,4
Women	42,6	42,0	46,6
Education			
None or elementary	5,1	4,7	8,1
Middle school	33,5	33,1	36,2
Professional School	10,2	10,4	9,0
High school	38,0	38,6	33,9
University degree or more	12,9	13,0	12,5
Age			
Up to 30	19,0	15,8	40,4
31-40	31,3	31,5	30,1
41-50	30,3	31,9	19,4
51-65	19,2	20,6	9,9
Firm size			
Up to 4	11,1	9,7	20,3
From 5 to 19	22,9	22,0	28,5
From 20 to 49	15,0	14,9	15,1
From 50 to 99	9,3	9,7	6,5
From 100 to 499	9,7	10,2	5,8
500 or more	10,2	10,7	7,3
Public sector	21,5	22,3	16,1
Region			
North-west	29,2	25,3	20,3
North-east	24,9	30,5	21,7
Centre	19,2	19,9	14,0
South	17,6	16,0	28,4
Islands	8,9	8,0	15,3
Occupation			
Blue collar	49,4	47,1	64,9
White collar	42,8	44,5	31,2
Manager	7,7	8,3	3,7
Industry			
Agriculture	4,5	3,5	11,6
Industry and mining	29,0	30,4	19,6
Building and construction	7,1	6,2	13,0
Wholesale and retail trade	11,8	11,4	14,5
Transport and communication	4,6	4,6	4,5
Credit and insurance	3,2	3,4	1,8
Business services	3,7	3,8	3,4
Domestic services	6,0	5,6	9,3
Public adiministration	29,4	30,5	21,6

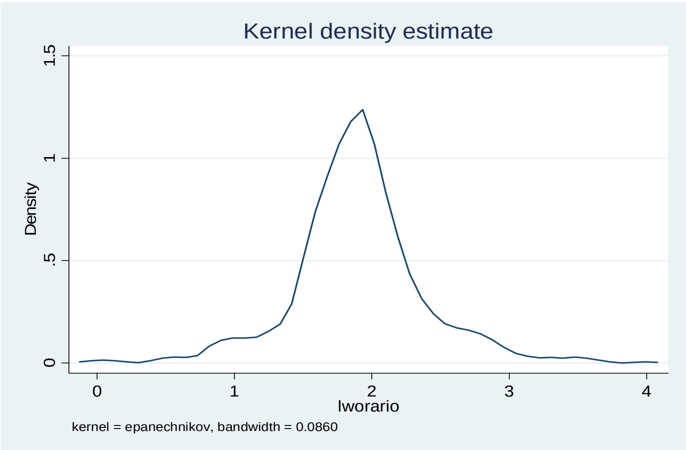
Note: Shiw, 2006

Tab.2: Percentiles of the log hourly wage for temporary and permanent workers

	Temporary	Permanent
Percentiles		
10%	1,42	1,76
25%	1,65	1,95
50%	1,90	2,14
75%	2,12	2,37
90%	2,44	2,66
0.9-0.1 spread	1,02	0,90
Mean	1,90	2,18
St. dev.	0,47	0,39
Obs.	646	4930

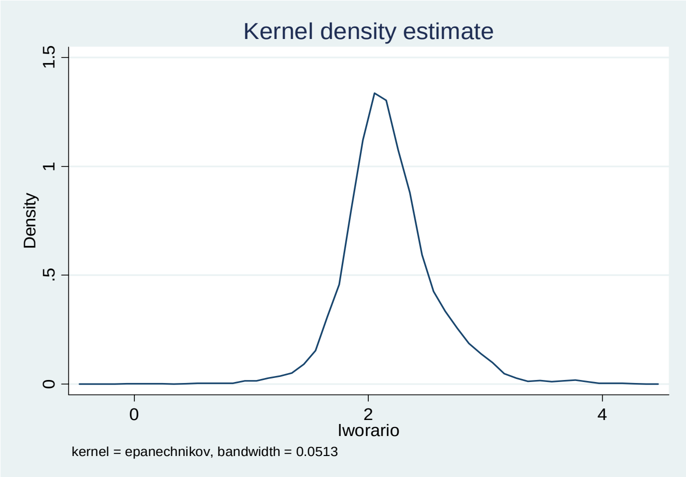
Note: Shiw, 2006

Fig.1a: Kernel density estimates of the wage distribution for temporary



Note: Epanechnikov kernel density estimates

Fig.1b: Kernel density estimates of the wage distribution for permanent



Note: Epanechnikov kernel density estimates

Tab.4: Quantile regression for wage gap between temporary and permanent workers

	Quantile				
	10th	25th	50th	75th	90th
Temporary	-0.207***	-0.133***	-0.113***	-0.064***	0.033
	(-6.16)	(-10.17)	(-10.92)	(-4.72)	(1.22)
Age	0.017	0.010**	-0.003	-0.014**	-0.007
	(2.09)***	(2.04)	(-0.83)	(-2.41)	(-0.89)
Age^2	0.000	0.000	0.000*	0.000***	0.000*
	(-1.69)*	(-1.49)	(1.84)	(3.14)	(1.89)
Experience	0.009**	0.006***	0.013***	0.013***	0.011**
	(2.64)	(2.64)	(4.51)	(3.67)	(2.53)
Experience^2	0.000**	-0.001**	-0.001***	0.001***	0.000***
	(-2.59)**	(-2.44)	(-5.15)	(-4.33)	(-3.49)
Tenure	0.006***	0.007***	0.004**	0.006***	0.001
	(2.66)	(6.44)	(2.47)	(3.36)	(0.61)
Tenure^2	-0.001	-0.001***	0.000	0.000	0.000
	(-1.45)	(-3.79)	(-0.91)	(-1.55)	(1.11)
Education					
University or more	0.220***	0.269***	0.365***	0.434***	0.477***
	(5.72)	(8.98)	(15.18)	(18.53)	(9.82)
High school	0.115***	0.115***	0.164***	0.182***	0.203***
	(3.49)	(4.21)	(10.26)	(9.69)	(7.05)
Professional school	0.092**	0.097***	0.103***	0.141***	0.190***
	(2.46)	(4.08)	(5.88)	(6.62)	(4.59)
Middle school	0.045	0.056**	0.064***	0.069***	0.091***
	(1.49)	(2.49)	(4.40)	(3.34)	(3.30)
Region					
North-West	-0.041***	-0.029***	-0.022***	-0.029*	-0.032**
	(-2.81)	(-2.77)	(-3.44)	(-1.66)	(-2.15)
Center	-0.053***	-0.024**	-0.013	-0.013	-0.01
	(-3.25)	(-2.04)	(-1.30)	(-0.86)	(-0.77)
South	-0.232***	-0.142***	-0.089***	-0.040**	-0.043*
	(-10.75)	(-15.10)	(-8.23)	(-1.98)	(-1.79)
Islands	-0.165***	-0.096***	-0.061***	-0.053***	-0.066***
	(-7.97)	(-4.65)	(-3.34)	(-2.68)	(-3.13)
Firm dimension					
From 5 to 19	0.159***	0.093***	0.089***	0.070***	0.061*
	(5.89)	(4.38)	(5.30)	(3.70)	(1.90)
From 20 to 49	0.166***	0.108***	0.106***	0.096***	0.112***
	(4.55)	(4.95)	(6.71)	(4.26)	(3.27)
From 50 to 99	0.224***	0.137***	0.120***	0.095***	0.083**
	(6.49)	(6.43)	(6.42)	(3.84)	(2.29)
From 100 to 499	0.205***	0.146***	0.167***	0.169***	0.170***
	(6.82)	(7.68)	(8.50)	(7.09)	(4.85)
Over 500	0.244***	0.189***	0.185***	0.183***	0.192***
	(7.36)	(10.77)	(9.01)	(6.28)	(5.56)
Occupation					
White collars	0.100***	0.103***	0.097***	0.101***	0.122***
	(5.92)	(7.42)	(9.21)	(9.64)	(6.90)
Public employees	0.278***	0.181***	0.198***	0.206***	0.194***
	(6.13)	(7.06)	(6.99)	(6.97)	(4.87)
Managers	0.183***	0.190***	0.207***	0.233***	0.273***
	(7.40)	(8.33)	(10.75)	(8.96)	(10.34)
Female	-0.109***	-0.099***	-0.092***	-0.091***	-0.076***
	(-7.80)	(-11.94)	(-10.03)	(-8.38)	(-3.69)
Married	0.031	0.031***	0.039***	0.036***	0.061***
	(1.52)	(2.94)	(4.07)	(2.91)	(2.75)
Head of Household	0.017	0.013	0.023***	0.029**	0.027
	(1.04)	(1.29)	(2.69)	(2.54)	(1.49)
Industry dummies	Yes	Yes	Yes	Yes	Yes

Note: the table reports coefficient estimates of different quantile regression and the test t are reported in parentesis.
*** Significant at the 1%, ** significant at the 5% and * significant at the 10%.

Tab.5: Quantile regression for wage gap between temporary and permanent workers, female

	Quantile				
	10th	25th	50°	75th	90th
Temporary	-0.145***	-0.099***	-0.082***	-0.044	0.043
	(-2.70)	(-3.78)	(-3.63)	(-1.48)	(0.57)
Age	0.023	0.004	-0.004	-0.001	0.006
	(1.61)	(0.40)	(-0.55)	(-0.15)	(0.55)
Age^2	0.000	0.000	0.000	0.000	0.000
	(-1.30)	(-0.12)	(1.19)	(0.66)	(0.13)
Experience	0.003	0.006	0.011***	0.011***	0.012
	(0.78)	(1.44)	(2.98)	(3.19)	(1.50)
Experience^2	0.000	0.000	-0.001***	0.000***	-0.001
	(-0.48)	(-1.26)	(-3.26)	(-3.24)	(-1.65)
Tenure	0.008**	0.009***	0.004**	0.006**	0.003
	(2.01)	(3.71)	(2.35)	(2.34)	(0.46)
Tenure^2	-0.001	0.000***	0.000	0.000	0.000
	(-1.33)	(-3.00)	(-0.27)	(-0.61)	(0.40)
Education					
University or more	0.281***	0.351***	0.405***	0.501***	0.461***
	(4.39)	(7.39)	(9.59)	(14.64)	(4.47)
High school	0.135**	0.148***	0.192***	0.221***	0.215**
	(2.23)	(4.04)	(5.96)	(7.86)	(2.49)
Professional school	0.086	0.094**	0.123***	0.146***	0.131
	(1.46)	(2.26)	(3.50)	(4.93)	(1.55)
Middle school	0.045	0.088***	0.092***	0.110***	0.114
	(0.81)	(2.69)	(3.20)	(4.74)	(1.27)
North-West	-0.039	-0.029*	-0.026*	-0.041**	-0.080*
	(-1.56)	(-1.69)	(-1.68)	(-2.35)	(-1.79)
Center	-0.033	-0.016	-0.006	0.016	-0.024
	(-0.74)	(-0.86)	(-0.33)	(0.78)	(-0.58)
South	-0.306***	-0.171***	-0.087***	-0.020	-0.038
	(-5.05)	(-8.78)	(-4.44)	(-0.70)	(-0.78)
Islands	-0.127**	-0.049	-0.044*	-0.054**	-0.129*
	(-2.13)	(-1.22)	(-1.93)	(-2.16)	(-1.92)
Firm dimension					
From 5 to 19	0.188***	0.141***	0.102***	0.081***	0.013
	(4.04)	(4.39)	(4.46)	(3.02)	(0.34)
From 20 to 49	0.165***	0.124***	0.095***	0.055**	0.063
	(2.76)	(4.47)	(4.32)	(2.29)	(1.31)
From 50 to 99	0.250***	0.181***	0.151***	0.142***	0.194***
	(5.19)	(6.43)	(5.76)	(6.11)	(3.51)
From 100 to 499	0.243***	0.169***	0.160***	0.144***	0.148***
	(4.30)	(5.68)	(7.58)	(4.36)	(3.04)
Over 500	0.234***	0.181***	0.167***	0.154***	0.102
	(4.48)	(4.30)	(4.23)	(4.13)	(1.47)
Occupation					
White collars	0.101***	0.113***	0.103***	0.115***	0.124***
	(4.06)	(5.41)	(5.53)	(7.66)	(3.88)
Public employees	0.314***	0.220***	0.210***	0.231***	0.161***
	(4.15)	(6.40)	(7.99)	(4.70)	(3.24)
Managers	0.150***	0.127***	0.183***	0.221***	0.184***
	(3.26)	(3.15)	(8.80)	(6.87)	(3.62)
Married	0.025	0.011	0.002	-0.007	-0.031
	(0.81)	(0.57)	(0.13)	(-0.36)	(-0.91)
Head of Household	0.019	0.007	0.006	-0.003	0.001
	(0.82)	(0.38)	(0.37)	(-0.20)	(0.03)
Industry dummies	Yes	Yes	Yes	Yes	Yes

Note: the table reports coefficient estimates of diffent quantile regression and the test t are reported in parentesis.
*** Significant at the 1%, ** significant at the 5% and * significant at the 10%.

Tab.6: Quantile regression for wage gap between temporary and permanent workers, male

	Quantile				
	10th	25th	50°	75th	90th
Temporary	-0.233***	-0.145***	-0.122***	-0.102***	0.003
	(-4.73)	(-6.04)	(-5.11)	(-4.45)	(0.06)
Age	0.017**	0.013*	-0.008	-0.021***	-0.023**
	(2.45)	(1.72)	(-1.08)	(-3.00)	(-2.55)
Age^2	-0.001**	-0.001	0.000	0.000***	0.000***
	(-2.01)	(-1.35)	(1.36)	(3.59)	(3.18)
Experience	0.004	0.006	0.013***	0.015***	0.016***
	(0.80)	(1.61)	(4.16)	(3.48)	(3.87)
Experience^2	0.000	-0.001*	-0.001***	-0.001***	-0.001***
	(-1.36)	(-1.95)	(-3.90)	(-4.26)	(-3.81)
Tenure	0.007***	0.007***	0.005***	0.004	0.002
	(2.75)	(5.38)	(3.20)	(1.47)	(0.57)
Tenure^2	0.000**	-0.001***	0.000**	0.000	0.000
	(-2.02)	(-3.30)	(-2.03)	(-0.64)	(0.52)
Education					
University or more	0.179***	0.225***	0.317***	0.319***	0.360***
	(3.75)	(4.83)	(10.79)	(6.76)	(5.59)
High school	0.095***	0.098***	0.134***	0.132***	0.117**
	(2.63)	(3.15)	(4.86)	(4.79)	(2.13)
Professional school	0.087**	0.110***	0.099***	0.123***	0.139**
	(2.18)	(2.86)	(3.85)	(3.57)	(2.28)
Middle school	0.046	0.057**	0.055***	0.043*	0.025
	(1.34)	(2.18)	(2.74)	(1.75)	(0.52)
North-West	-0.068***	-0.022	-0.010	-0.012	-0.047**
	(-3.19)	(-1.12)	(-0.71)	(-0.63)	(-2.06)
Center	-0.054**	-0.025**	-0.016	-0.013	-0.013
	(-2.34)	(-2.20)	(-1.22)	(-0.73)	(-0.41)
South	-0.218***	-0.118***	-0.075***	-0.060**	-0.070**
	(-7.70)	(-7.15)	(-3.80)	(-2.15)	(-2.25)
Islands	-0.190***	-0.114***	-0.068***	-0.049	-0.076*
	(-5.97)	(-4.64)	(-2.88)	(-1.39)	(-1.82)
Firm dimension					
From 5 to 19	0.099*	0.047	0.067***	0.053**	0.025
	(1.97)	(1.48)	(4.57)	(2.43)	(0.50)
From 20 to 49	0.117**	0.084***	0.107***	0.095***	0.084*
	(2.29)	(2.75)	(6.54)	(4.25)	(1.84)
From 50 to 99	0.152***	0.090***	0.080***	0.046	-0.002
	(2.78)	(3.98)	(4.79)	(1.63)	(-0.05)
From 100 to 499	0.154***	0.112***	0.165***	0.173***	0.154***
	(3.13)	(2.92)	(8.15)	(6.25)	(3.25)
Over 500	0.202***	0.155***	0.186***	0.190***	0.149***
	(3.43)	(5.78)	(7.95)	(6.06)	(3.05)
Occupation					
White collars	0.112***	0.116***	0.111***	0.111***	0.147***
	(5.50)	(6.42)	(6.45)	(5.52)	(6.68)
Public employees	0.205***	0.140***	0.161***	0.179***	0.174***
	(3.21)	(3.09)	(6.02)	(5.55)	(2.98)
Managers	0.224***	0.234***	0.245***	0.279***	0.343***
	(10.23)	(9.36)	(11.25)	(7.86)	(8.21)
Married	0.057***	0.040***	0.065***	0.064**	0.063**
	(2.93)	(3.39)	(4.02)	(2.56)	(2.22)
Head of Household	0.018	0.016	0.029**	0.045***	0.040
	(0.77)	(1.52)	(2.19)	(4.57)	(1.31)
Industry dummies	Yes	Yes	Yes	Yes	Yes

Note: the table reports coefficient estimates of diffent quantile regression and the test t are reported in parentesis.
*** Significant at the 1%, ** significant at the 5% and * significant at the 10%.

Tab. 7: Quantile wage regression with selectivity correction, female

	Quantile				
	10th	25th	50°	75th	90th
Temporary	-0.129**	-0.091***	-0.093***	-0.037	0.058
	(-2.16)	(-3.65)	(-3.52)	(-1.47)	(0.98)
Age	0.026	0.005	-0.005	0.001	0.003
	(1.50)	(0.44)	(-0.76)	(0.15)	(0.23)
Age^2	0.000	0.000	0.000	0.000	0.000
	(-1.32)	(-0.17)	(1.51)	(0.43)	(0.35)
Experience	0.002	0.010**	0.014***	0.011**	0.015***
	(0.38)	(2.24)	(4.35)	(2.56)	(2.76)
Experience^2	0.000	0.000*	0.000***	0.000**	-0.001***
	(-0.19)	(-1.93)	(-4.64)	(-2.81)	(-3.18)
Tenure	0.008*	0.007**	0.003	0.003	0.003
	(1.91)	(2.30)	(1.22)	(1.27)	(0.54)
Tenure^2	0.000	-0.001*	0.000	0.000	0.000
	(-1.27)	(-1.88)	(0.24)	(0.06)	(0.36)
Education					
University or more	0.289***	0.352***	0.407***	0.514***	0.471***
	(4.95)	(7.54)	(11.25)	(11.86)	(5.63)
High school	0.127**	0.151***	0.185***	0.227***	0.224***
	(2.49)	(4.19)	(7.11)	(7.20)	(3.77)
Professional school	0.092	0.108***	0.124***	0.151***	0.144**
	(1.61)	(2.66)	(4.48)	(4.04)	(2.18)
Middle school	0.028	0.086***	0.086***	0.106***	0.123**
	(0.52)	(2.60)	(3.65)	(4.05)	(2.38)
North-West	-0.045*	-0.038*	-0.015	-0.032**	-0.075**
	(-1.72)	(-1.95)	(-1.05)	(-2.00)	(-2.45)
Center	-0.028	-0.018	0.003	0.025	-0.030
	(-0.86)	(-0.83)	(0.16)	(0.98)	(-0.68)
South	-0.329***	-0.174***	-0.081***	-0.013	-0.019
	(-5.65)	(-5.49)	(-3.45)	(-0.43)	(0.47)
Islands	-0.138**	-0.044	-0.027	-0.041	-0.146***
	(-2.39)	(-1.07)	(-1.19)	(-1.22)	(-2.75)
Firm dimension					
From 5 to 19	0.185***	0.142***	0.104***	0.069***	0.019
	(3.48)	(5.34)	(4.93)	(3.20)	(0.47)
From 20 to 49	0.157**	0.113***	0.073***	0.053**	0.066
	(2.19)	(3.81)	(3.27)	(2.04)	(1.37)
From 50 to 99	0.258***	0.186***	0.158***	0.151***	0.189***
	(4.85)	(5.86)	(6.60)	(4.06)	(3.13)
From 100 to 499	0.242***	0.152***	0.150***	0.120***	0.164**
	(3.95)	(4.77)	(5.35)	(3.22)	(2.48)
Over 500	0.232***	0.174***	0.166***	0.146***	0.127**
	(5.26)	(5.24)	(5.10)	(4.18)	(2.07)
Occupation					
White collars	0.078**	0.095***	0.085***	0.108***	0.113***
	(2.56)	(5.42)	(5.13)	(4.24)	(3.52)
Public employees	0.310***	0.228***	0.205***	0.218***	0.158***
	(5.13)	(8.01)	(7.17)	(4.24)	(3.43)
Managers	0.113**	0.102***	0.163***	0.210***	0.186***
	(2.28)	(3.23)	(4.30)	(4.60)	(3.00)
Married	0.047**	0.033**	0.030*	0.32*	0.010
	(2.12)	(2.24)	(1.69)	(1.73)	(0.30)
Head of Household	0.036	0.032*	0.035**	0.022	0.030
	(1.62)	(1.86)	(2.11)	(1.00)	(0.96)
Mills ratio	-0.183	-0.113	-0.087	-0.074	-0.030
	(-1.08)	(-1.02)	(-1.06)	(-0.70)	(-0.16)
Mills ratio^2	0.089	0.024	0.015	0.006	-0.025
	(0.85)	(0.31)	(0.30)	(0.11)	(-0.18)
Industry dummies	Yes	Yes	Yes	Yes	Yes

Note: the table reports coefficient estimates of diffent quantile regression and the test t are reported in parenthesis. Bootstrap standard errors are obtained with 50 replications. *** Significant at the 1%, ** significant at the 5% and * significant at the 10%.

Tab 8: Quantile wage regression with selectivity correction, male

	Quantile				
	10th	25th	50°	75th	90th
Temporary	-0.197***	-0.139***	-0.121***	-0.085***	0.006
	(-3.40)	(-6.10)	(-5.94)	(-3.18)	(0.09)
Age	0.020**	0.009	-0.009*	-0.021**	-0.030**
	(2.00)	(1.19)	(-1.70)	(-2.60)	(-2.27)
Age^2	-0.001*	0.000	0.000**	0.000***	0.001***
	(-1.70)	(-1.00)	(2.06)	(2.93)	(2.74)
Experience	0.004	0.008**	0.015***	0.015***	0.016***
	(0.97)	(2.21)	(5.47)	(3.52)	(2.61)
Experience^2	-0.001	0.000**	-0.001***	-0.001***	-0.001***
	(-1.11)	(-2.40)	(-4.69)	(-3.81)	(-3.10)
Tenure	0.007**	0.005**	0.004**	0.003	0.002
	(2.15)	(2.58)	(1.98)	(1.13)	(0.53)
Tenure^2	-0.001	0.000*	0.000	0.000	0.000
	(-1.40)	(-1.74)	(-1.31)	(-0.58)	(0.21)
Education					
University or more	0.181***	0.232***	0.314***	0.325***	0.378***
	(4.41)	(4.92)	(11.26)	(5.93)	(6.10)
High school	0.099***	0.085***	0.121***	0.128***	0.114***
	(2.76)	(3.26)	(5.49)	(2.94)	(2.60)
Professional school	0.095***	0.091***	0.085***	0.120***	0.146***
	(2.78)	(3.14)	(3.07)	(2.66)	(2.92)
Middle school	0.053*	0.041	0.046**	0.043	0.026
	(1.69)	(1.62)	(2.46)	(1.10)	(0.69)
North-West	-0.070***	-0.031**	-0.015	-0.019	-0.040**
	(-3.66)	(-2.44)	(-1.31)	(-1.05)	(-2.16)
Center	-0.047**	-0.019	-0.014	-0.008	-0.006
	(-2.35)	(-1.35)	(-0.93)	(-0.45)	(-0.22)
South	-0.217***	-0.119***	-0.073***	-0.059***	-0.066**
	(-7.24)	(-5.84)	(-4.31)	(-3.06)	(-2.02)
Islands	-0.177***	-0.111***	-0.067***	-0.040	-0.053
	(-7.34)	(-4.64)	(-2.94)	(-1.63)	(-1.32)
Firm dimension					
From 5 to 19	0.104***	0.047*	0.071***	0.057**	0.041
	(3.18)	(1.96)	(4.00)	(2.22)	(1.02)
From 20 to 49	0.133***	0.085***	0.110***	0.099***	0.108**
	(4.01)	(2.94)	(5.74)	(3.56)	(2.19)
From 50 to 99	0.167***	0.094***	0.80***	0.050	0.021
	(4.42)	(3.21)	(4.11)	(1.64)	(0.56)
From 100 to 499	0.170***	0.113***	0.166***	0.163***	0.163***
	(4.29)	(3.62)	(9.36)	(5.25)	(3.52)
Over 500	0.216***	0.159***	0.187***	0.196***	0.182***
	(4.75)	(5.91)	(7.83)	(5.50)	(3.83)
Occupation					
White collars	0.109***	0.108***	0.107***	0.108***	0.131***
	(3.83)	(5.29)	(8.44)	(6.73)	(4.05)
Public employees	0.225***	0.122***	0.177***	0.178***	0.197***
	(5.23)	(3.30)	(6.88)	(4.24)	(4.17)
Managers	0.226***	0.219***	0.238***	0.271***	0.318***
	(7.17)	(7.26)	(9.55)	(7.38)	(6.35)
Married	0.073***	0.058***	0.073***	0.076***	0.052**
	(3.68)	(3.57)	(6.25)	(4.36)	(2.24)
Head of Household	0.043***	0.029**	0.045***	0.062***	0.030
	(2.61)	(2.43)	(4.39)	(4.97)	(1.33)
Mills ratio	-0.044	-0.178**	-0.084	-0.178**	-0.263*
	(-0.34)	(-1.99)	(-1.13)	(-1.98)	(-1.81)
Mills ratio^2	-0.022	0.120*	0.034	0.104	0.124
	(-0.17)	(1.71)	(0.68)	(1.36)	(1.07)
Industry dummies	Yes	Yes	Yes	Yes	Yes

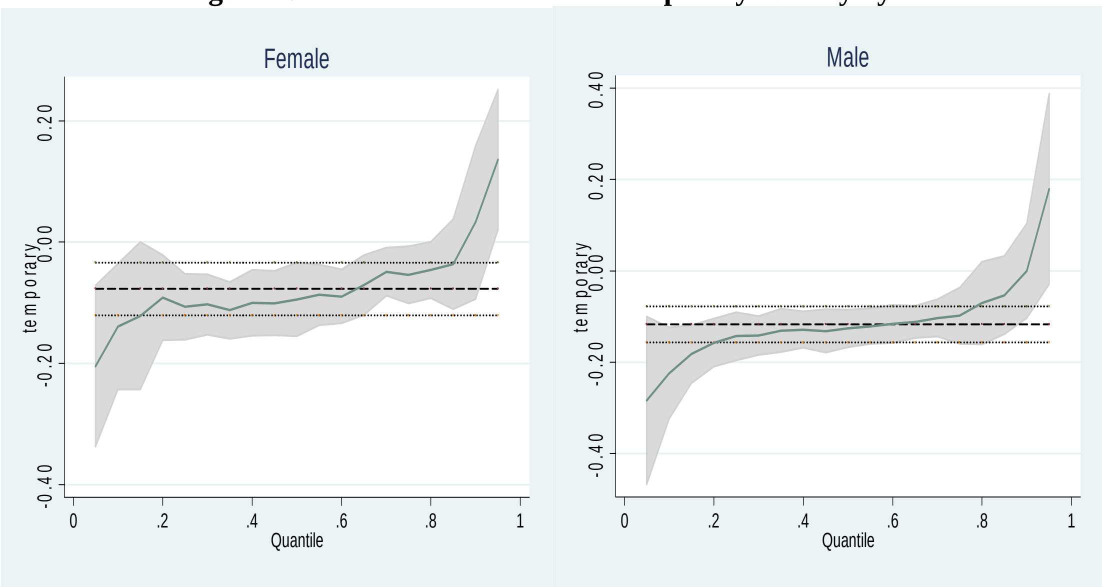
Note: the table reports coefficient estimates of diffent quantile regression and the test t are reported in parenthesis. Bootstrap standard errors are obtained with 50 replications. *** Significant at the 1%, ** significant at the 5% and * significant at the 10%.

Tab. 9: Quantile regression (Machado-Mata) decomposition of the wage differentials between temporary and permanent workers

	Without selectivity correction			With selectivity correction		
	All sample	Female	Male	All sample	Female	Male
Quantile 0.10						
Raw differences	-0.378	-0.405	-0.361	-0.375	-0.406	-0.355
Characteristics	-0.168	-0.169	-0.166	-0.181	-0.178	-0.166
Coefficients	-0.209	-0.235	-0.194	-0.193	-0.227	-0.189
Quantile 0.20						
Raw differences	-0.309	-0.317	-0.300	-0.304	-0.311	-0.299
Characteristics	-0.161	-0.153	-0.159	-0.173	-0.162	-0.165
Coefficients	-0.147	-0.164	-0.141	-0.131	-0.149	-0.133
Quantile 0.30						
Raw differences	-0.287	-0.278	-0.286	-0.287	-0.276	-0.289
Characteristics	-0.158	-0.152	-0.152	-0.167	-0.160	-0.164
Coefficients	-0.128	-0.125	-0.134	-0.119	-0.116	-0.125
Quantile 0.40						
Raw differences	-0.272	-0.252	-0.274	-0.271	-0.254	-0.275
Characteristics	-0.159	-0.154	-0.152	-0.167	-0.161	-0.164
Coefficients	-0.112	-0.098	-0.122	-0.104	-0.092	-0.111
Quantile 0.50						
Raw differences	-0.265	-0.241	-0.274	-0.263	-0.244	-0.276
Characteristics	-0.160	-0.160	-0.154	-0.166	-0.165	-0.167
Coefficients	-0.105	-0.080	-0.120	-0.097	-0.079	-0.109
Quantile 0.60						
Raw differences	-0.261	-0.225	-0.283	-0.261	-0.231	-0.285
Characteristics	-0.162	-0.162	-0.156	-0.168	-0.166	-0.167
Coefficients	-0.098	-0.063	-0.127	-0.093	-0.064	-0.118
Quantile 0.70						
Raw differences	-0.259	-0.211	-0.290	-0.258	-0.214	-0.288
Characteristics	-0.168	-0.173	-0.161	-0.170	-0.171	-0.167
Coefficients	-0.091	-0.037	-0.128	-0.088	-0.043	-0.120
Quantile 0.80						
Raw differences	-0.241	-0.183	-0.285	-0.244	-0.187	-0.279
Characteristics	-0.177	-0.186	-0.163	-0.176	-0.181	-0.167
Coefficients	-0.064	0.002	-0.122	-0.068	-0.006	-0.111
Quantile 0.90						
Raw differences	-0.176	-0.139	-0.223	-0.180	-0.152	-0.223
Characteristics	-0.184	-0.209	-0.161	-0.181	-0.203	-0.168
Coefficients	0.007	0.070	-0.062	0.001	0.050	-0.055

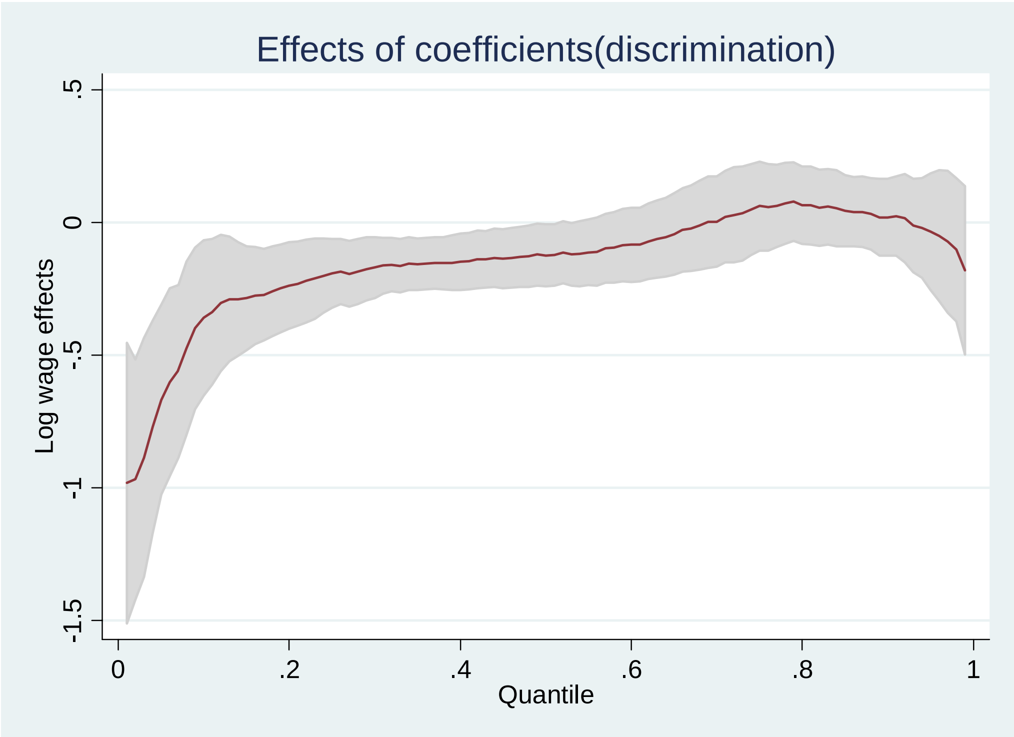
Note: Shiw, 2006. Machado-Mata decomposition, using Melly (2006) estimator.

Figure 2: Coefficient estimates for temporary dummy by sex



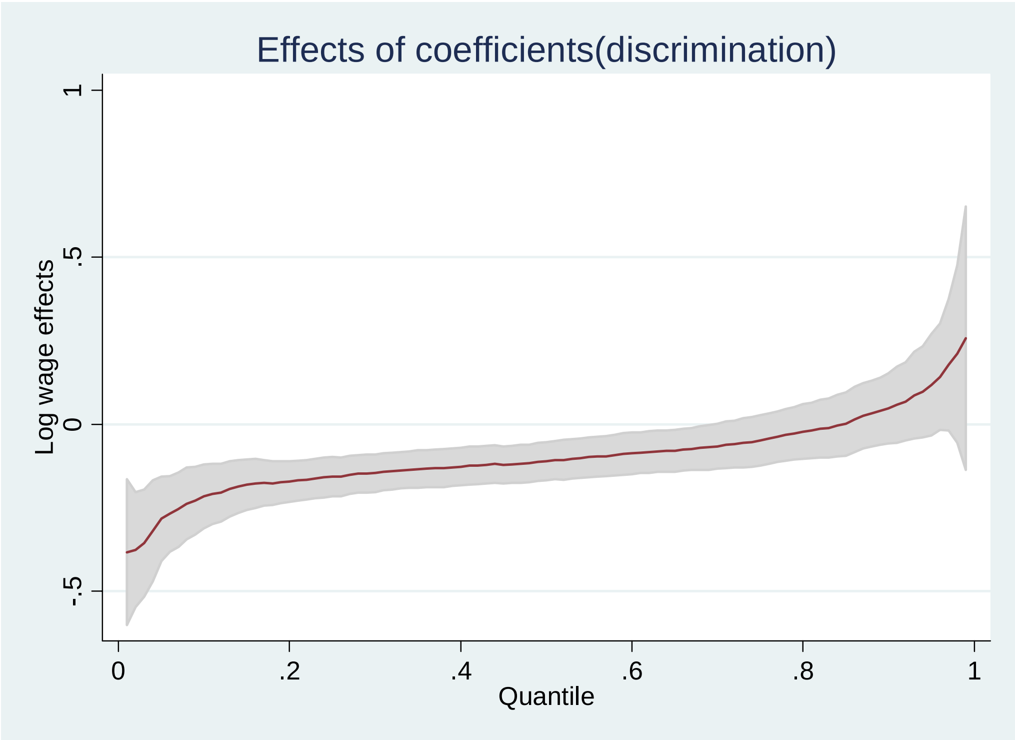
Note: confidence intervals extend to 95% in either direction. Horizontal lines represent OLS estimates with 95% confidence intervals.

Fig. 3a: price differential by educational level, university



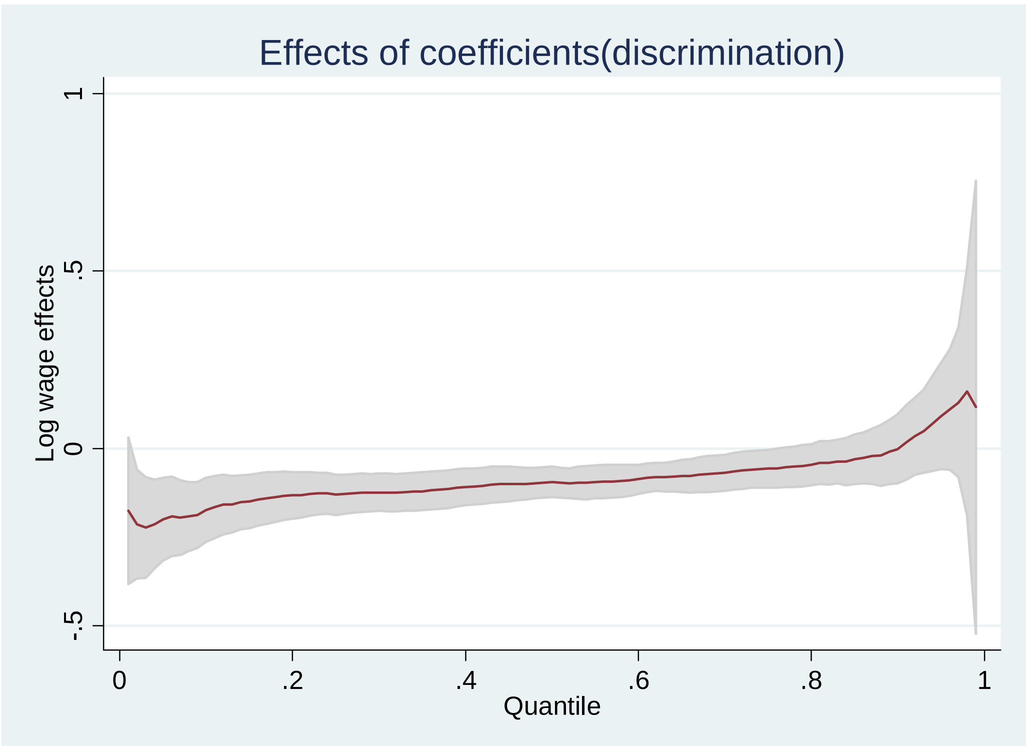
Note: Machado and Mata decomposition. Variables controlled for in the regression are age, experience, tenure, marital status, household dummies, firm size, occupation, region.

Fig. 3b: price differential by educational level, high and professional school



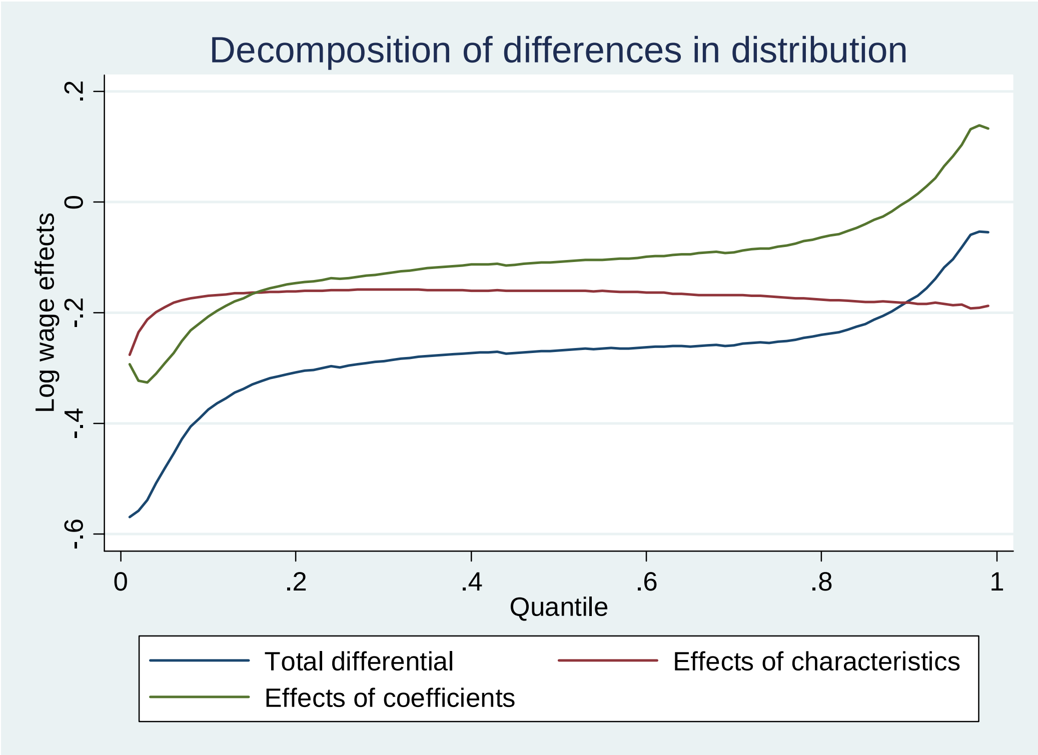
Note: Machado and Mata decomposition. Variables controlled for in the regression are age, experience, tenure, marital status, household dummies, firm size, occupation, region.

Fig. 3c: price differential by educational level, middle and elementary school



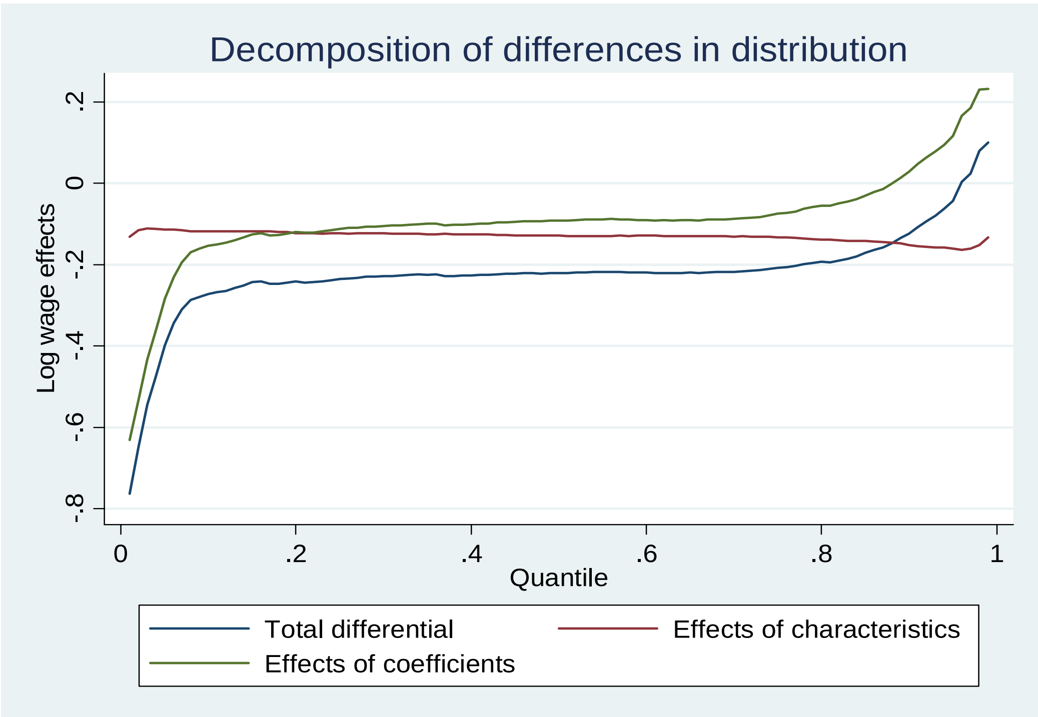
Note: Machado and Mata decomposition. Variables controlled for in the regression are age, experience, tenure, marital status, household dummies, firm size, occupation, region.

Fig. 3: Machado-Mata decomposition for young workers (16-35 years)



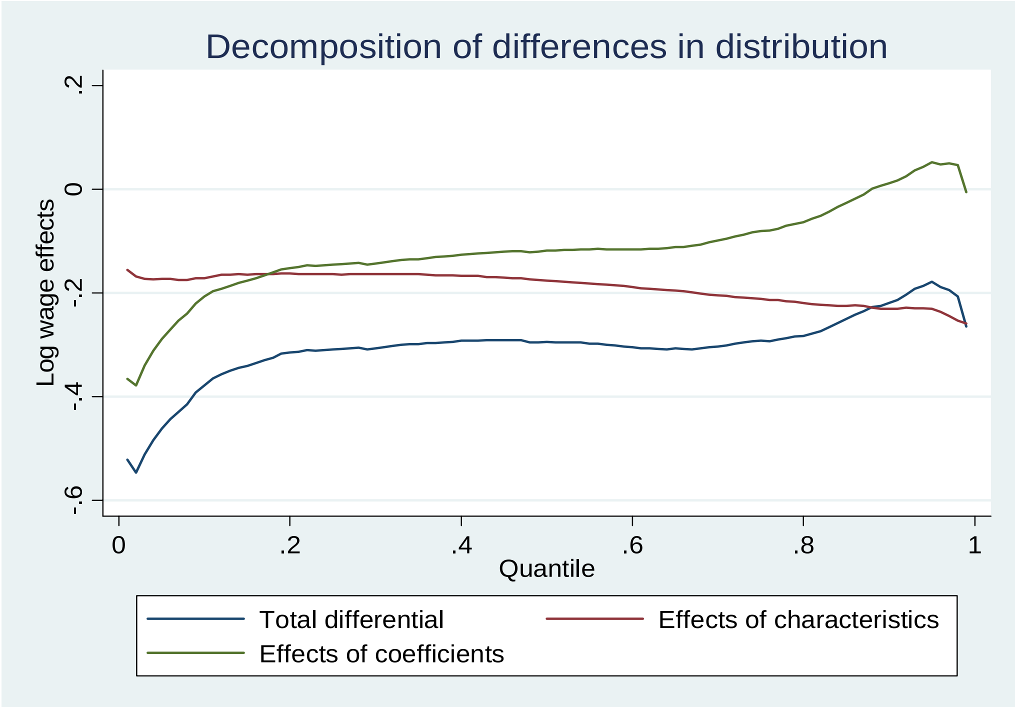
Note: Machado and Mata decomposition. Variables controlled for in the regression are age, experience, tenure, marital status, household dummies, firm size, occupation, region.

Fig 4: Machado-Mata decomposition for the workers resident in the North



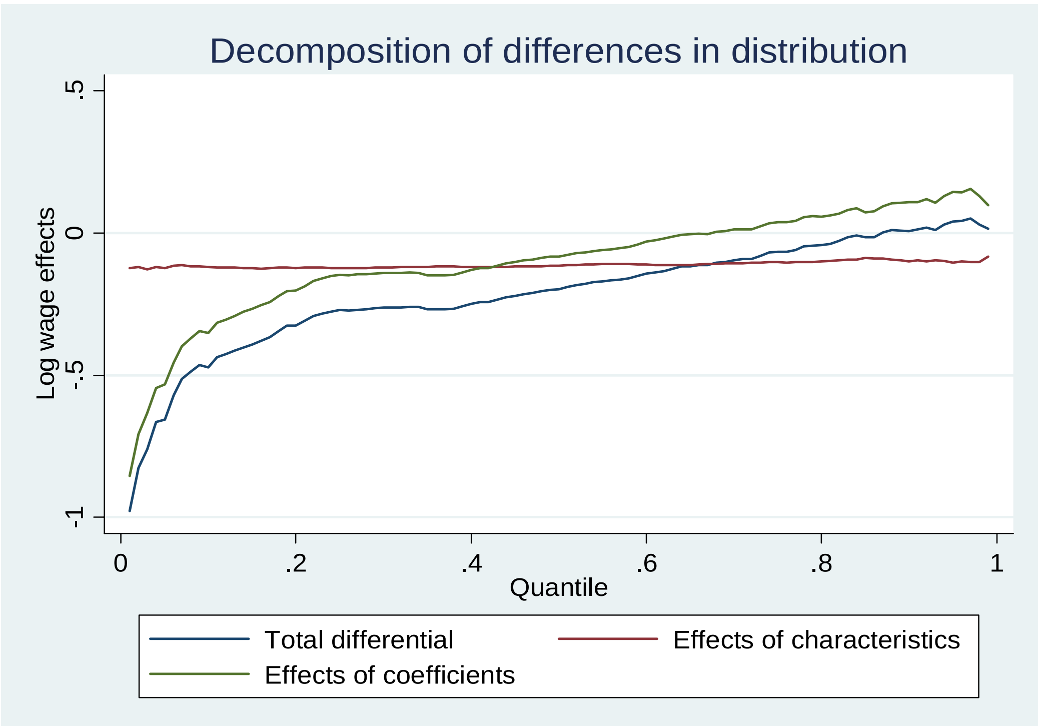
Note: Machado and Mata decomposition. Variables controlled for in the regression are age, experience, tenure, marital status, household dummies, firm size, occupation.

Fig 5: Machado-Mata decomposition for the workers resident in the South



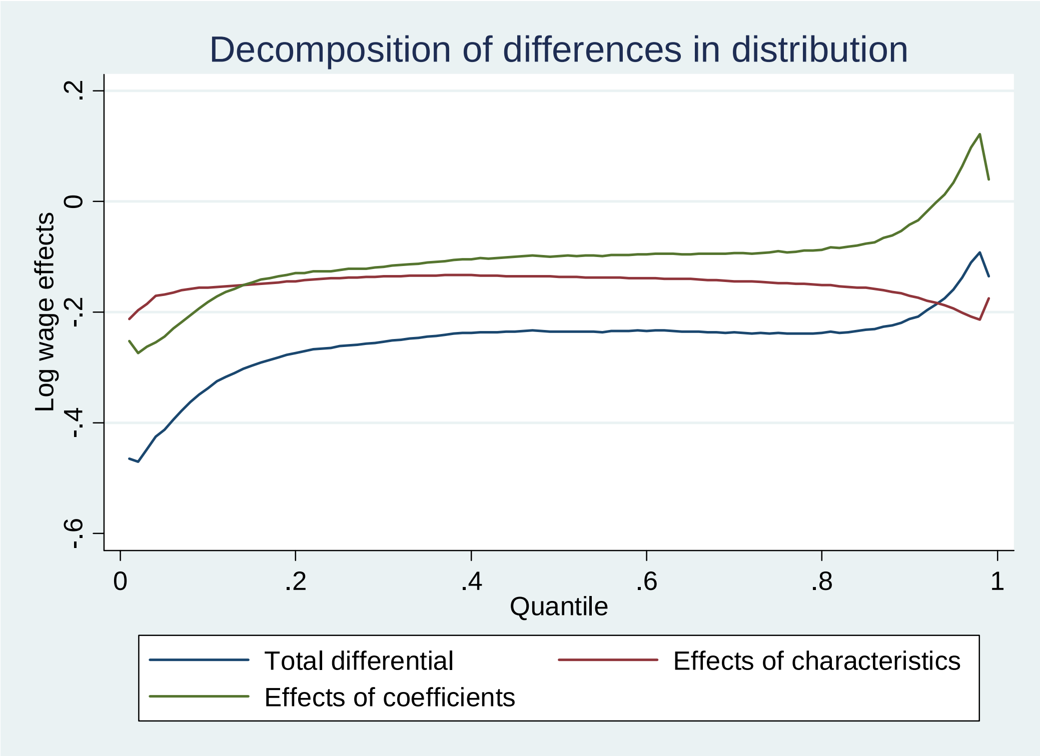
Note: Machado and Mata decomposition. Variables controlled for in the regression are age, experience, tenure, marital status, household dummies, firm size, occupation.

Fig 6: Machado-Mata decomposition for the workers in public sector



Note: Machado and Mata decomposition. Variables controlled for in the regression are age, experience, tenure, marital status, household dummies, firm size, occupation, region.

Fig 7: Machado-Mata decomposition for the workers in private sector



Note: Machado and Mata decomposition. Variables controlled for in the regression are age, experience, tenure, marital status, household dummies, firm size, occupation, region.

Table 9: IV quantile treatment effect of temporary status

	10th	25th	50th	75th	90th
			Female		
2SLAD	-0.044 (-0.84)	-0.067** (-2.37)	-0.043* (-1.71)	-0.039 (-1.30)	-0.022 (-0.49)
QTE with individual variables	-0.430*** (-4.01)	-0.364*** (-5.84)	-0.312*** (-5.21)	-0.292*** (-5.56)	-0.208** (-2.28)
QTE with individual and occupation variables	-0.265** (-2.25)	-0.173** (-2.33)	-0.164*** (-2.60)	-0.127 (-1.58)	-0.010 (-0.08)
			Male		
2SLAD	-0.061 (-1.51)	-0.046* (-1.91)	-0.056*** (-2.73)	-0.071*** (-3.02)	-0.069* (-1.81)
QTE with individual variables	-0.344*** (-3.65)	-0.244*** (-5.07)	-0.201*** (-4.46)	-0.178*** (-2.69)	-0.090 (-0.75)
QTE with individual variable	-0.218** (-2.15)	-0.170*** (-2.84)	-0.144*** (-2.71)	-0.151** (-2.16)	-0.098 (-0.80)

Note: the Quantile Treatment Effect estimator applies the Abadie, Angrist and Imbens (2002). The IVQR (2LAD and QTE) standard errors are obtained via bootstrapping with 100 replications. *** Significant at 1%, ** at 5% and * at 10%.

Table 10: Summary of the Estimation Resuls

	Quantile				
	10th	25th	50th	75th	90th
			Female		
Quantile regression	-0.145*** (-2.70)	-0.099*** (-3.78)	-0.082*** (-3.63)	-0.054* (-2.57)	0.043 (0.57)
QTE (1)	-0.430*** (-4.01)	-0.364*** (-5.84)	-0.312*** (-5.21)	-0.292*** (-5.56)	-0.208** (-2.28)
QTE (2)	-0.265** (-2.25)	-0.173** (-2.33)	-0.164*** (-2.60)	-0.127 (-1.58)	-0.010 (-0.08)
Self-selection model (1)	-0.129** (-2.16)	-0.091*** (-3.65)	-0.093*** (-3.52)	-0.037 (-1.47)	0.058 (0.98)
Self-selection model (2)	-0.152*** (-3.64)	-0.099*** (-4.12)	-0.090*** (-3.68)	-0.063** (-2.51)	0.033 (0.46)
			Male		
Quantile regression	-0.233*** (-4.73)	-0.145*** (-6.04)	-0.122*** (-5.11)	-0.102*** (-4.45)	0.003 (0.06)
QTE (1)	-0.344*** (-3.65)	-0.244*** (-5.07)	-0.201*** (-4.46)	-0.178*** (-2.69)	-0.090 (-0.75)
QTE (2)	-0.218** (-2.15)	-0.170*** (-2.84)	-0.144*** (-2.71)	-0.151** (-2.16)	-0.098 (-0.80)
Self-selection model (1)	-0.197*** (-3.40)	-0.139*** (-6.10)	-0.121*** (-5.94)	-0.085*** (-3.18)	0.006 (0.09)
Self-selection model (2)	-0.217*** (-4.84)	-0.140*** (-4.71)	-0.123*** (-6.28)	-0.096*** (-4.04)	0.004 (0.07)

Note: Standard errors are obtained via bootstrapping with 100 replications, test t are reported in parenthesis *** Significant at 1%, ** at 5% and * at 10%.QTE (1) controls only for individual variable, while QTE (2) also for job characteristics. Self-selection model (1) is identified through exogenous instrument (searching) while self-selection model (2) relies only on non linearity of selectivity correction term.