FRIEDRICH-ALEXANDER-UNIVERSITÄT ERLANGEN-NÜRNBERG

Lehrstuhl für VWL, insbes. Arbeitsmarkt- und Regionalpolitik
Professor Dr. Claus Schnabel

Diskussionspapiere
Discussion Papers

No. 105

The Age Pay Gap and Labor Market Heterogeneity: A New Empirical Approach Using Data for Italy

MARINA TÖPFER

JULY 2018

ISSN 1615-5831

Editor: Prof. Dr. Claus Schnabel, Friedrich-Alexander-Universität Erlangen-Nürnberg

The Age Pay Gap and Labor Market Heterogeneity: A New Empirical Approach Using Data for Italy*

Marina Töpfer†
University of Erlangen-Nuremberg, School of Business and Economics, Germany

Abstract: Using Italian microdata over the period 2005-2016, this paper studies the difference in pay between elderly (55-64) and adult (34-54) workers in Italy along the wage distribution. The estimation strategy consists in using a three-way fixed effects wage model and adjusting the wage gap for (observed and unobserved) labor market heterogeneity. The estimation relies on OLS as well as on unconditional quantile regressions. The analysis beyond the mean shows substantial differences in the age pay gap along the wage distribution and finds particularly pronounced gaps at the top. The fixed effects of interest (individual, job and industry) are estimated via a partitioned procedure. Adjusting the gap for labor market heterogeneity reduces the gap almost to zero. The results suggest that individual differences between the cohorts both observed and unobserved are the main driver of the gap.

Zusammenfassung: Dieser Beitrag untersucht das Lohndifferenzial zwischen älteren (55-64) und erwachsenen (34-54) Arbeitsmarktteilnehmern entlang der Lohnverteilung anhand italienischer Mikrodaten 2005-2016. Die Lohngleichung basiert auf einem 'three-way fixed effects' Modell. Der Beitrag betrachtet die um (beobachtbare und nicht-beobachtbare) Arbeitsmarktheterogenität korrigierte Lohnlücke. Das Lohndifferenzial wird mit OLS und unbedingter Quantilsregression geschätzt. Die drei fixen Effekte (individuell, job- und industriespezifisch) werden mit Hilfe einer Partitionierungsmethode geschätzt. Die Analyse entlang der Lohnverteilung zeigt substanzielle Unterschiede in dem Lohndifferenzial an verschiedenen Quantilen. Dabei ist die Lohnlücke am oberen Ende der Lohnverteilng besonders ausgeprägt. Der Beitrag zeigt, dass individuelle Heterogeneität der Hauptverursacher der Lohnlücke ist und die korrigierte Lohnlücke gegen Null geht.

Keywords: Age Pay Gap, Three-Way Fixed Effects Model, Decomposition, Italy.
JEL - Classification: J7, J14, J310

*For data provision, I thank Emiliano Mandrone and the Italian Institute for the Development of Vocational Training for Workers (Isfol). For helpful comments and suggestions, I am grateful to Luisa Rosti, Claus Schnabel, Pawel Bukowski, Vahagn Jerbashian and Jan Rutkowski as well as participants in the 2017 IBS Jobs Conference in Warsaw.

†Correspondence to: University of Erlangen-Nuremberg, School of Business and Economics, Chair of Labor and Regional Economics, Lange Gasse 20, 90403 Nuremberg. E-mail: marina.toepfer@fau.de.

1 Introduction

A phenomenon of modern labor markets is the increasing share in elder labor market participants, commonly referred to as aging. This phenomenon becomes more and more important as the process of aging is increasing in speed (e.g. Cardoso et al., 2011). One reason for an increasingly aging population are better health conditions and reductions in birth rates in developed countries (OECD, 2016). Since earnings increase over the life-cycle with labor market experience and therefore age, there are positive and significant differences in pay between elder and adult labor market participants. On the contrary, productivity may not increase with age (e.g. Lazear, 1979; Loewenstein and Sicherman, 1991; Avolio and Waldman, 1994; Skirbekk, 2004; de Hek and van Vuuren, 2011). As productivity is difficult to measure, productivity-driven differences across cohorts would imply Age Pay Gaps (APGs) that are mainly unexplained based on observable characteristics. As social tensions may be created in the case of wage schemes perceived as unfair, it is of interest to study age-related pay gaps.

So far, little research focuses on explaining pay differences by age (Lazear, 1981; Rosolia and Torrini, 2007). The literature has rather concentrated on changes in productivity profiles over the life-cycle (e.g. Avolio and Waldman, 1994; McCue, 1996; Skirbekk, 2004; Walker and Zhu, 2003). This paper uses a new empirical approach to explain the APG in Italy using microdata. The contribution of this paper is two-fold. First, the applied estimation strategy catches otherwise unobserved heterogeneity at the worker-, job- and industry-level. Second, to the author's best knowledge, this study is the first that considers the Italian APG along the wage distribution.

The seminal paper of Lazear (1979) motivated a lot of research on pay and productivity differentials along the age-dimension. Aubert and Crépon (2003) and Huck et al. (2011) find support for Lazear's model of deferred compensation and evidence against the human capital on-the-job training model, i.e. performance-based pay. In the model of deferred compensation, workers are underpaid at the beginning of their careers and overpaid at the end. In particular, employers face imperfect information on the workers' performance and workers and firms are engaged in long-term relationships. On-the-job training includes both formal and informal training. Workers in training are less productive, what imposes a cost to the employer. Yet, this lower level of productivity at time t is accepted in exchange for higher productivity at time $t + 1$. An age-related wage-productivity gap may also arise from union bargaining as unions support generally wage increases with seniority (de Hek and van Vuuren, 2011). The results in the literature on productivity differences between elder and adult workers are ambiguous. For example, Skirbekk (2004) suggests that the decline in average productivity starts approximately at the age of 50, while Avolio and Waldman (1994) find that productivity starts to decline at the age of 30.

Age-related differences in the labor market are highly debated in Italy.[1] The debate can be summarized by the perception that Italy is a country of the elder. In the past, early retirement was used as an instrument to resolve economic crises in Italy (Disney, 2000; Massimiliano et al., 2017) leading to a relative low share of elder workers in the Italian labor market compared to other OECD countries (OECD, 2013). This policy has also made the Italian pension system one

[1]Several journals treated this topic. For example articles published in 'Il Giornale', 'Espresso-Repubblica' or 'Libero Quotidiano' entitled: "Italy is the paradise of the elderly but an inferno for the younger" – *"L'Italia è il paradiso degli anziani ma per i giovani è un inferno"* (19-10-2017), "Locust Generation, Italy in the hands of the elderly [...]" –*"Generazione locuste, Italia in mano agli anziani [...]"* (12-6-2015) or "Italy is a country for the elder [...]" –*"L'Italia è un paese per vecchi [...]"* (17-05-2012), respectively.

of the most expensive and thereby increased the burden on the younger generations to prevent the social security and pension system from collapsing. Hence, wage dispersion between cohorts represents a potential source of social conflict in Italy.

The main objective of this analysis is to investigate whether the positive APG between elder (55-64 years) and adult (34-54 years) workers is due to favoritism of elder workers or discrimination of adult workers in the labor market or whether it can be explained by labor market heterogeneity. Favoritism arises if elder employees engage in 'influence activity' to alter supervisors' decisions in their favor (Milgrom and Roberts, 1988) or there may be favoritism on behalf of supervisors for particular workers (Prendergast and Topel, 1996). In fact, group identity is found to be pivotal in explaining discrimination (Mc Dermott, 2009). Chen and Li (2009) conduct lab experiments to measure the effect of group identity on social preferences. Their results support the hypothesis that individuals favor matches of their own group.

Three factors may be particularly important for explaining pay differences by age; worker, industrial and job heterogeneity. Individual heterogeneity captures, beyond observable (time-constant) characteristics like schooling or gender, also differences in the motivation and attitude to work that may change over cohorts (Galenson and Weinberg, 2000). Individual productivity depends on the workers ability and attitude towards work as well as on his or her labor market experience and educational attainment (e.g. McCue, 1996; Skirbekk, 2004; Cardoso et al., 2011; Walker and Zhu, 2003). The latter two can be easily controlled for using microdata while ability and attitude or motivation to work are omitted as unobserved. Moreover, sector differences in unionization or organization of work lead to worker-specific allocation to industries. Finally, employee segregation may also occur at the job-level.

An important issue that has so far been neglected in the estimation of the APG is the variation of the gap along the wage distribution. Unions may be particularly strong at the median and bottom (median voter argument) and hence age-group based wage increases may be particularly pronounced for these points of the wage distribution. The APG may be smaller at the top as only the most productive and presumably best-motivated adult workers make it to the top (before automatic promotion based on seniority becomes effective). However, given a decentralization process of collective bargaining and the switch to more performance-related pay mechanisms in Italy (Russo, 2007; Bordogna and Neri, 2012), individual differences may play a crucial role as well. In order to detect this potential inequality for different income groups, a quantile regression approach is applied. We use the linear Unconditional Quantile Regression (UQR) model and add the above mentioned three sources of labor market heterogeneity to the model. Using decomposition techniques, we then obtain an estimate of the adjusted APG for different quantiles. We use the linear UQR model or the Recentered Influence Function (RIF) OLS as so far only UQRs allow to obtain path-independent detailed Blinder-Oaxaca type decompositions (Fortin et al., 2011). We are interested in the aggregate APG as well as in the gap adjusted for different sources of labor market heterogeneity. Therefore, we need to calculate the contribution of the three sources of labor market heterogeneity to the wage gap. A major difference between the Conditional Quantile Regression (CQR) and the UQR model is that it is defined conditional on the set of regressors, while UQRs define the quantiles before the regression (see Martins and Pereira, 2004; Machado and Mata, 2005; Autor et al., 2008; Antonczyk et al., 2010, for applications of CQRs). Consequently, the dependent variable, the RIF, is not influenced by any right-hand-side variables in the RIF-OLS model.

In the empirical analysis, we calculate first the raw or unadjusted APG at the mean as well as at different quantiles. The average wage gap is large, amounting to 16.6%, and increasing along the wage distribution (from 6% at the 10th quantile to 34.3% at the 90th quantile).

Rosolia and Torrini (2007) find a gap of approximately 20% between 31-35 and 51-60 year-old employees in Italy over the period 1984-2004. Second, we decompose the gap accounting for labor market experience, its square and job tenure that may represent the natural advantage of elderly over adult workers. We use the pooled wage structure (Neumark, 1988) over the entire sample, i.e. 18-64 years, as non-discriminatory wage structure. The wage structure is thus based on the theoretical background in Lazear (1979) stating that individuals are not discriminated or favored over their career path and thus 'net' discrimination against the groups is zero. We find that the APG is mainly due to its unexplained component at the mean, median and top of the wage distribution. Consequently, the gap cannot be explained by labor market experience and tenure at these points of the distribution. The Fixed Effects (FEs) of generally unobserved heterogeneity are estimated by partitioning the estimation of the regression in different sets of equations and solving each equation separately (Gaure, 2010; Guimaraes and Portugal, 2010). Adjusting the APG for labor market heterogeneity reduces the gap substantially and suggests favoritism of elder workers at the bottom of the distribution.

This paper is organized as follows. Section 2 outlines the institutional background in Italy. In Section 3 the data is described. Next, the estimation strategy and the results obtained are presented in Section 4 and 5, respectively. In Section 6, we run several robustness checks. Section 7 concludes.

2 The Case of Italy

The case of Italy may be particularly interesting given strong unions and especially pronounced social security burdens on younger generations. At the same time, we observe a decentralization process of collective bargaining and public employment in Italy (Russo, 2007; Bordogna and Neri, 2012). These factors may affect the cohorts differently (Brandolini, 2005; Contini and Trivellato, 2005) and more flexible wage-setting mechanisms may result in wage premiums of generally unobserved characteristics at the individual level such as motivation or commitment to work. Since the 1990s several labor market reforms in Italy aiming at the creation of a more flexible labor market resulted in a dual labor market along the age-dimension (Brandolini, 2005; Contini and Trivellato, 2005). Entry wages were reduced and hiring was made more flexible (leading to an increase in temporary contracts). Thus, these reforms may prevent long-term employment relationships. The burden for the younger cohorts is particularly high as they are more likely to hold temporary contracts and are more exposed to employment loss (Crepaldi et al., 2014).

In Italy (and worldwide), the aging process is also highly debated in the context of an increasing burden on the social security system. The political debate is particularly concerned with the decline in the old-age support ratio, i.e. the number of those capable of providing economic support to the number of elder people that may be materially dependent on the support of others (OECD, 2013). In particular, Italy had the most expensive pension system within the OECD at the end of the last decade and an effective age of labor market exit that is the fourth lowest (OECD, 2013). In order to secure the sustainability of the pension system, reforms were implemented.[2] The reforms included an increase in the seniority-based retirement

[2] A major pension reform has been adopted in late 2011 in Italy (Law 214/2011). Main elements of the reform are the abolition of the early retirement option, adaptation of men's and women's retirement age and the linking of the increase in life expectancy and age as well as seniority requirements attempting to substantially reduce pension expenditures.

age and inaugurated a policy of renunciation from early retirement as a way to solve economic crisis (Disney, 2000; Massimiliano et al., 2017).

In order to fight the recent crisis, beyond the increase in retirement age, attempts to reduce employee protection were made. In particular, public services and public-sector employment have been an important target of government policies. Levels of employment, wage and salary increases as well as pension systems have been in the focus of repeated austerity measures adopted by the government (Bordogna and Neri, 2012). In the 2010-2012 bargaining round, wages in the public sector were frozen. On the one hand, this may have led to a de-motivation or a more negative work attitude affecting the cohorts differently. Recruitment and promotion stops may have hit the adult cohort more severe than the elder cohort. On the other hand, increased risk of job destruction and firing may have increased the commitment to work particularly of the adult cohort.

Changes in the organization of collective bargaining and automatic promotion stops in public employment may have affected the age-related wage gap in Italy as well. Italy has strong unions and automatic promotion mechanisms that trigger automatic wage increases with age and hence the APG. According to the literature, unionism contributes to higher wage levels and job stability as well as to automatic mechanisms of wage progression (Pencavel, 1991). However, decentralized wage bargaining is associated with higher wage inequality (OECD, 2004) .

All of these factors (degree of unionism, national retirement strategies, promotion of specific groups in the labor market) influence the presence, the wage level as well as the commitment to work of elder and adult workers differently. Especially the younger cohorts are hit by the above mentioned reforms. Therefore they may contribute to positive and unexplained pay disparities between adult and elder workers.

3 Data

The data set used in this study is the survey ISFOL Plus from the Italian Institute for Development of Vocational Training of Workers (ISFOL) – see Corsetti and Mandrone (2012). In the investigation, all waves available are used, i.e. data over the period 2005-2016. So far, the survey has been conducted in 2005, 2006, 2008, 2010, 2011, 2014 and 2016. We keep male full-time workers aged 34-64 years. We consider adult and elder workers in order to investigate the effects of the dual labor market along the age-dimension on the APG. We define elder workers as individuals aged 55-64 following the definition of older workers of the European Parliament and the Italian government (Crepaldi et al., 2014). According to OECD (2017), adult workers are individuals from mid-30s to mid-50s. Female workers are dropped as the individual variation based on gender would be absorbed by the individual FE. The gap would then also be explained by gender-based discrimination. As we know from the literature that gender discrimination on the labor market matters (see for example the seminal work of Becker, 2010) and in order to catch the effect of individual variation not based on gender, we focus on male workers. However, as a robustness test, we test our results on the female subsample as well as on the full sample of men and women (see Section 6). Given wage freezes in the public sector, we repeat the analysis also for male public servants only.

We observe 21,042 positive wage observations of full-time male workers aged 34-64. The sample is then restricted to the largest connected set (identified via the algorithm proposed by Weeks and Williams, 1964), what leaves us with 16,440 positive wage observations. We need to restrict the sample to the largest connected set as in this set all FEs are connected. This allows us to compare the estimated FEs with each other (Cardoso et al., 2016). In the sample, 6,035 individuals belong to the group aged 55-64 years and 10,405 individuals to the group aged 34-54 years.

We do not have linked employer-employee data and hence do not have information on the employer side (e.g. firm FEs). Even though we cannot identify single firms in our data and hence we are not able to control for firm FEs directly, firms and industry FEs are collinear, as the same firm is engaged in the same industry. Therefore, we expect to catch effects of firm sorting via industry sorting.

Each individual entering the survey is assigned a unique identifying wave number. This allows us to follow the individual over time and to identify the corresponding industry and occupation the individual holds in each wave. Industry specifications are based on Ateco 15 (settore attività economica), i.e. in total we have 16 industry controls. Nine distinct occupations are defined. The job categories and industrial classification are not as narrowly defined as it is generally the case with linked employer-employee data. However, we observe sufficient variation across jobs. More than 50% of elder and adult workers change their job cells (see Table 1).

Table 1 presents the descriptive statistics. A detailed description of the variables used in the analysis along with their coding can be found in Table A.1 in the Appendix. Table 1 shows that there is a substantial raw APG of 16.6 percentage points in the underlying sample for Italy. The adult subsample contains more observations than the elder subsample, which is, first, a result of the larger range of the adult sample $\in [34, 54]$ compared to the elder age group $\in [55, 64]$. Second, it is driven by the fact that the effective age of labor market exit in Italy is the fourth lowest within the OECD (OECD, 2013).Workers that cross the age bracket (34-54) to (55-64) account for 30% of the sample. That is, we observe 4,916 workers aging and thus can capture the aging process of the workforce. Hence, the estimates are mainly based on individual variation due to aging.[3] In each cohort more than half of the individuals change industry or job. As expected, labor market experience and job tenure are higher for the elderly. Elder and adult employees are relatively equal in terms of educational attainment. However, there are substantially more elder workers with a university degree (*Educ_4*). This may be counter intuitive given increases in human capital over the last decades (e.g. Godin, 2014). Looking at the sample of workers in and out of employment, however, we observe more adult than elder graduates (see Table 2, Panel A).

Table 3 shows the summary statistics of the worker FEs. These FEs are estimated via the iterative procedure proposed by Guimaraes and Portugal (2010) and outlined in Section 4. The estimation procedure does not allow to disentangle productivity from motivation or commitment to work; these effects are all included in the set of individual FEs. Hence, we observe only the direction of the aggregate effect of individual-specific characteristics that is higher for the elderly compared to the adult group. The variation in the set of worker FEs at different quantiles underlines that it is important to look at changes along the wage distribution and not only at the mean. There are substantial differences in the set of individual heterogeneity between the generations. The difference is particularly pronounced at the 90th quantile. The set is higher for elder workers compared to adults. This supports the hypothesis that elder labor-market participants have higher commitment to work that may outperform potential lower productivity levels assumed in the model of Lazear (1979).

[3] Consequently, even though, we have only half the length of the panel in Cardoso et al. (2011), we can capture the process of aging relatively well.

Table 1: Descriptive Statistics

	(1)	(2)	(3)	(4)
	Elderly		Adult	
Variable	Mean	Std.Dev.	Mean	Std.Dev.
Hourly Wage (in logs)	2.372	0.471	2.207	0.397
Experience (years)	35.37	5.625	26.72	7.573
Tenure (years)	27.35	10.23	19.18	9.720
Educ_1 Dummy	0.024	0.154	0.015	0.120
Educ_2 Dummy	0.152	0.359	0.246	0.431
Educ_3 Dummy	0.474	0.499	0.522	0.500
Educ_4 Dummy	0.350	0.477	0.218	0.413
Public_Sector Dummy	0.613	0.487	0.409	0.492
Married Dummy	0.761	0.427	0.789	0.408
North Dummy	0.370	0.483	0.475	0.499
Centre Dummy	0.203	0.403	0.186	0.389
Movers across Age Bracket	30.0%			
Industry Movers	52.0%		54.7%	
Job Movers	50.3%		54.1%	
Observations	6,035		10,405	

Table 2: Descriptive Statistics Education and Public Sector Dummies, Different Samples

	(1)	(2)	(3)	(4)
	Elderly		Adult	
Variable	Mean	Std.Dev.	Mean	Std.Dev.
Panel A: Sample Workers and Out of Employment				
Educ_1 Dummy	0.246	0.431	0.016	0.127
Educ_2 Dummy	0.438	0.496	0.235	0.424
Educ_3 Dummy	0.219	0.413	0.508	0.500
Educ_4 Dummy	0.219	0.413	0.241	0.428
Observations	44,726		38,246	
Panel B: Sample Not Restricted to Largest Connected Set				
Public_Sector Dummy	0.525	0.499	0.359	0.479
Observations	7,870		13,172	

Notes: The table shows the descriptive statistics of the education dummies on the sample of individuals both in work and out of work (including unemployed and individuals out of the labor force).
For the public-sector dummy, the descriptive statistics using the sample not restricted to the largest connected set are shown.
Both samples contain only men.

Table 3: Summary Statistics, Worker FEs at the Mean and Different Quantiles

	(1)	(2)	(3)	(4)	(5)
	Elderly		Adult		
Quantile	Mean	Std.Dev.	Mean	Std.Dev.	Difference
Mean	0.214	0.380	0.056	0.321	0.158
10	0.023	0.288	-0.013	0.336	0.036
50	0.069	0.330	-0.040	0.339	0.109
90	0.246	1.097	-0.143	0.731	0.389
Observation	6,035		10,405		16,440

Notes: The Table shows the worker FEs that have been estimated using the partitioned procedure by Guimaraes and Portugal (2010) at different points of the wage distribution.

4 Estimation Strategy

In order to estimate and decompose the APG, we first set-up a basic wage model that accounts for labor market experience and job tenure as well as time FEs. In a second step, we calculate the Recentered Influence Function (RIF) for the estimation beyond the mean. Next, we estimate the FEs and add them to the base model, what gives us a three-way FEs or the full model. The base and full model are estimated separately for adult and elder workers and decomposed in an explained and unexplained part. The raw APG is then adjusted for individual heterogeneity, job and industry sorting. Finally, the contribution of these three sources of labor market heterogeneity to the gap is estimated using a detailed decomposition approach.

The base model looks as follows:

$$y_{it} = x_{it}\beta^{base} + \delta_t + \epsilon_{it}^{base} \tag{1}$$

with x_{it} having dimension $1 \times K$ and including labor market experience, its square and job tenure. β^{base} contains the corresponding coefficients. A set of time dummies is contained in δ_t, the error term ϵ_{it}^{base} is assumed to follow the standard assumptions. The dependent variable y_{it} is the natural logarithm of the net hourly wage. The indices i, t identify the worker $(i = 1 \dots N)$ and time period $(t = 1 \dots T)$, respectively.

In order to extend the analysis beyond the mean, we use linear UQRs. Therefore, we estimate the RIF (Firpo et al., 2009) defined as:

$$RIF(Y_t; q_\tau) = q_\tau + \frac{\tau - \mathbb{1}\{Y_t \leq q_\tau\}}{f_{Y_t}(q_\tau)} \tag{2}$$

where q_τ is the value of the log hourly wage, Y, at the quantile, τ in period t. $f_{y_t}(q_\tau)$ is the density of Y_t at q_τ. We calculate the year-specific RIF in order to account for changes in the wage distribution over time (see e.g. DiNardo et al., 1996). The quantile-specific wage model is then estimated by running equation (1) with the RIF as dependent variable.[4]

In the next step, we estimate a linear model with three additional FEs following Guimaraes and Portugal (2010) and Gaure (2010) in order to account for heterogeneity. We assume that the omitted variables are constant over time. The procedure allows to identify the point estimates of the FEs without having to invert the matrices but by using an iterative procedure. For identification of the sample of the largest connected set, the algorithm proposed by Weeks and Williams (1964) is used. The sample is then restricted to this set. In the largest connected set, all FEs are connected ensuring comparability of the estimated FEs (Cardoso et al., 2016). We then calculate the following FEs and add them to the base model (1):

- Workers FEs (= workers' permanent heterogeneity, ψ_i)
- Job FEs (=job titles' permanent heterogeneity, ϕ_j)
- Industry FEs (=industries' permanent heterogeneity, λ_d)

The indices i, j, d identify the worker $(i = 1 \dots N)$, job $(j = 1 \dots J)$ and industry category $(d = 1 \dots D)$. These FEs have been omitted in the base model. The full model reads then as:

$$y_{ijdt} = x_{it}\beta^{full} + \delta_t + \psi_i + \phi_j + \lambda_d + \epsilon_{ijdt}^{full} \tag{3}$$

[4] We use the Gaussian kernel and the Silverman optimal bandwidth.

where ψ_i, ϕ_j and λ_d are the FEs that have been omitted in the base model (1). All permanent individual heterogeneity is captured by the set ψ_i. That is in ψ_i, beyond standard controls like schooling, also generally unobservable characteristics are caught such as the attitude or motivation towards work and individual productivity. For example, we catch now actual experience and not only potential work experience. Regan and Oaxaca (2009) shows that using potential instead of actual experience causes specification error in wage models. The vector β^{full} contains the coefficients of the explanatory variables in x. In matrix notation, the model has the following form:

$$Y = X\beta^{full} + G\delta + E\psi + J\phi + D\lambda + \epsilon \tag{4}$$

where Y is the $N^* \times 1$ vertically stacked vector of wages sorted by t, i, j, d and $N^* = K + T + N + J + D$. The total number of parameters that we want to estimate amounts to N^*. G is a $N^* \times T$ design matrix of time dummies, E is a $N^* \times N$ design matrix of worker FEs, J is a $N^* \times J$ design matrix of job indicators and D is a $N^* \times D$ design matrix of industry FEs. Time-varying characteristics are contained in the $N^* \times K$ matrix X.

For estimation of the three FEs, we estimate the full model via the algorithm proposed by Guimaraes and Portugal (2010). The procedure allows to obtain exact OLS solutions without having to invert the matrices. The idea is to alternate between the estimation of the parameters of the model. The partitioned iterative procedure consists in an alternative approach to the standard estimation problem reducing the dimensionality of the data. We estimate five linear regressions with K covariates and compute group means of residuals:

$$\begin{pmatrix} \beta^{full} & = & (X'X)^{-1}X'(Y - G\delta - E\phi - J\psi - D\lambda) \\ \delta & = & (G'G)^{-1}G'(Y - X\beta^{full} - E\psi - J\phi - D\lambda) \\ \psi & = & (E'E)^{-1}E'(Y - X\beta^{full} - G\delta - J\phi - D\lambda) \\ \phi & = & (J'J)^{-1}J'(Y - X\beta^{full} - G\delta - E\psi - D\lambda) \\ \lambda & = & (D'D)^{-1}D'(Y - X\beta^{full} - G\delta - E\psi - J\phi) \end{pmatrix}$$

We just iterate between these equations and obtain exact least squares solutions. The estimated coefficients for X are the same as the parameter estimates obtained from the standard regression on X and four sets of dummy variables or a standard FEs model with three sets of dummy variables.[5] The advantage of this approach is, beyond the reduction in dimensionality, that we can now easily calculate the adjusted APG as the three FEs are simply added to the base model as additional regressors. Similarly, we can calculate the contribution of the distinct set of FEs to the gap.

As individual, job, and industry heterogeneity may not be constant over time, we further estimate the full model with first-differenced FEs (Addison et al., 2015). The full model in FDs looks then as:

$$y_{it} = x_{it}\beta^{full} + \delta_t + \Delta\psi_i + \Delta\phi_j + \Delta\lambda_d + \epsilon_{it}^{full} \tag{5}$$

with $\Delta\psi_i = \psi_{it} - \psi_{it-1}$, $\Delta\phi_j = \phi_{jt} - \phi_{jt-1}$ and $\Delta\lambda_d = \lambda_{dt} - \lambda_{dt-1}$. As the survey is conducted with different regularity, the time differences caught go from one lag (e.g. 2006-2005) up to two lags (e.g. 2016-2014).

[5] See Table A.2 in the Appendix for an application.

Decomposition Analysis

In order to obtain estimates of the unadjusted as well adjusted APG and the part of the gap that cannot be explained by differences in characteristics, we conduct a decomposition analysis based on Blinder (1973) and Oaxaca (1973). We use the pooled wage structure β^* as reference category (Neumark, 1988). The coefficient estimates β^* are obtained from a wage regression on the entire sample. The intuition behind is that over the life-cycle the individuals are not discriminated or favored (Lazear, 1979). The decomposition of the base model reads as:

$$\begin{aligned}\bar{Y}_E - \bar{Y}_A &= \bar{X}_E \hat{\beta}_E^{base} - \bar{X}_A \hat{\beta}_A^{base} \\ &= \underbrace{(\bar{X}_E - \bar{X}_A)\beta^*}_{\text{Explained Part}} + \underbrace{\bar{X}_E(\hat{\beta}_E^{base} - \beta^*) - \bar{X}_A(\hat{\beta}_A^{base} - \beta^*)}_{\text{Unexplained Part}} \end{aligned} \quad (6)$$

where $\{A, E\}$ identifies the group of adult (A) and elderly (E) workers, respectively. That is, for the decomposition, we run the regression of the wage model separately by age cohort. We estimate equation (7) with both the OLS and RIF-OLS model and then adjust it for the three FEs:

$$\begin{aligned}\bar{Y}_E - \bar{Y}_A &= \bar{X}_E \hat{\beta}_E^{full} - \bar{X}_A \hat{\beta}_A^{full} + \underbrace{(\psi_i^E + \phi_j^E + \lambda_d^E) - (\psi_i^A + \phi_j^A + \lambda_d^A)}_{\Delta\text{FE}} \\ \bar{Y}_E - \bar{Y}_A - \Delta\text{FE} &= \underbrace{(\bar{X}_E - \bar{X}_A)\beta^*}_{\text{Explained Part}} + \underbrace{\bar{X}_E(\hat{\beta}_E^{full} - \beta^*) - \bar{X}_A(\hat{\beta}_A^{full} - \beta^*)}_{\text{Unexplained Part}} \\ &= \bar{X}_E \hat{\beta}_E^{full} - \bar{X}_A \hat{\beta}_A^{full} \end{aligned} \quad (7)$$

In order to calculate the contribution of individual heterogeneity to the APG, we conduct a detailed decomposition, which consists in calculating the contribution of the single covariates to the raw gap (see Jann, 2008, for details).

5 Estimation Results

The raw or unadjusted APG amounts to 16.6 % (log approximation) in Italy in the period 2005-2016 (see Table 4). That is adult workers earn on average one-sixth less than elder workers. The gap varies along the wage distribution. Figure 1 shows that the APG is almost linearly increasing from the bottom to the top of the distribution. The unexplained component of the unadjusted APG is the part that is often referred to as discriminatory part. The unexplained part accounts here for the part of the gap that cannot be explained with differences between the cohorts in labor market experience, its square and job market tenure. Hence, it is not a proper estimate for discrimination as unobserved characteristics like favoritism as well as observed characteristics like schooling are not included in the estimation of the base model. The unexplained component beyond favoritism may also capture deferred compensation or the institutional background. It makes-up the main part of the APG at the median and top of the wage distribution. In contrast, it is negligible at the bottom. At the mean the gap based on differences in prices is 6.6 percentage points lower compared to the raw gap. At the 50th quantile, the gap is reduced by almost 50% (see Table 4, Panel A). The remaining part is due to group differences in labor market experience and job tenure. The positive unexplained part for middle- and top-income earners suggests favoritism of the elder over the adult cohort in the middle and at upper parts of the wage distribution. The detailed decomposition of the full model is shown in Panel B of

Table 4. It reveals that individual FEs alone account for 16 percentage points of the raw APG at the mean. Industry and job FEs account for 0.2 and 0.1 percentage points, respectively. At the 10th quantile 3.5, at the median 1.1 and 3.9 percentage points at the top are due to personal heterogeneity. Consequently, individual labor market heterogeneity both unobserved and observed explains the major part of the APG at different points of the wage distribution.

Figure 2 shows the unadjusted and adjusted APGs along the wage distribution. The gap adjusted by the three FEs is close to zero throughout the wage distribution. Hence, controlling for job and industry sorting as well as personal characteristics that catch, beyond standard time-constant individual-level variation (such as schooling), individual productivity, motivation and commitment to work, reduces the APG substantially. If one assumes that adult and elderly workers employed in the same industry and doing the same job, face the same institutional framework and have equal ability or productivity, a positive APG corrected for permanent labor market heterogeneity can be referred to as 'favoritism' of elder workers. This may imply that elder employees engage in 'influence activity' to change supervisors' decisions in their favor (Milgrom and Roberts, 1988) or that supervisors may favor particular workers (Prendergast and Topel, 1996).

The gap is statistically insignificant at the mean and median of the wage distribution (Table 4, Panel B). Thus, for middle-income earners, we find no evidence for favoritism of elder workers. Contrary, at the top of the wage distribution, the adjusted gap is negative and statistically significant. This remaining part constitutes a gap that cannot be explained by differences in individual characteristics or job and industry sorting. The negative gap implies that the raw gap is smaller than the gap in labor market heterogeneity. At the bottom a positive and statistically significant gap remains and hence in this case, the raw gap is larger than differences in personal-, job- or industry-level heterogeneity. This suggests favoritism of elder workers at the lower part of the wage distribution. Individual variation allows to explain almost the entire APG and the unexplained portion of the adjusted gap approximates zero.

Changes in workers' individual heterogeneity over time are not captured by individual FEs. Endogeneity of changes in this set including generally unobserved characteristics may bias the results. Similarly, specific industries or jobs may face external shocks (both positive or negative) that lead workers to move in or away from these industries or jobs as well as employers to hire or fire workers. Both may result in increases in adult industry or job movers. Therefore, we estimate the adjusted APG using first-differenced FEs. The gap adjusted by FDs is also corrected substantially downwards. As expected, we loose a significant amount of observations when considering FDs (see Table 4, Panel C). This suggests that the set of individual FEs is mainly time constant. Only for 23% of the sample, the set of worker FEs changes over time. Using FDs, we find a positive gap at the mean and bottom that cannot be explained based on worker, job-title or industry heterogeneity. At all other points, the wage gap can be entirely explained by labor market heterogeneity. The detailed decomposition of the full model with FDs shows again that individual heterogeneity is the most important driver of the APG. For median- to high-income earners, this suggests that characteristics other than productivity that are generally unobserved but awarded with a wage premium in the labor market (such as commitment or motivation to work) outweigh the lower or declining effect of productivity of the elderly as assumed in the literature (Lazear, 1979; Cardoso et al., 2011). Contrary, for adult workers, higher levels of productivity are not enough to make up for lower levels in other characteristics. Eventually, this leads to higher sets of individual FEs for elder workers (as shown in Table 3).

Using UQRs has shown that there are substantial differences in the APG along the wage

Table 4: Decomposition at the Mean and Selected Quantiles, Pooled Wage Structure

	(1)	(2)	(3)	(4)
	Mean	10	50	90
Panel A: Unadjusted Decomposition				
Raw Difference	0.166***	0.060***	0.135***	0.353***
	(0.009)	(0.008)	(0.009)	(0.025)
Unexplained	0.101***	-0.005	0.070***	0.288***
	(0.008)	(0.008)	(0.008)	(0.023)
Observations	16,440	16,440	16,440	16,440
Panel B: FEs Adjusted Decomposition				
Adjusted	0.003	0.021**	0.020	-0.031*
	(0.018)	(0.025)	(0.016)	(0.041)
Detailed Decomposition of the Raw APG:				
Contribution of FE1	0.160***	0.035***	0.110***	0.389***
	(0.002)	(0.00009)	(0.0003)	(0.003)
Contribution of FE2	0.001***	0.002***	0.001***	0.004***
	(0.000001)	(0.0000005)	(0.000003)	(0.000002)
Contribution of FE3	0.002***	0.003***	0.005***	-0.008***
	(0.000004)	(0.000001)	(0.000001)	(0.000004)
Observations	16,440	16,440	16,440	16,440
Panel C: FDs Adjusted Decomposition				
Adjusted	0.017**	0.030***	0.023	-0.037
	(0.020)	(0.023)	(0.018)	(0.046)
Detailed Decomposition of the Raw APG, Sample of FDs:				
Contribution of FE1	0.162***	0.033***	0.112***	0.395***
	(0.000001)	(0.000005)	(0.000003)	(0.000002)
Contribution of FE2	0.001***	0.002***	0.001***	0.004***
	(0.000001)	(0.000005)	(0.000003)	(0.000002)
Contribution of FE3	0.001***	0.003***	0.005***	-0.008***
	(0.000004)	(0.000001)	(0.000001)	(0.000004)
Observations	3,819	3,780	3,780	3,780

Robust standard errors in parentheses for OLS
Boostrapped standard errors in parentheses (500 replications) for UQRs
Standard errors clustered at the individual level
$***p < 0.01, **p < 0.05, *p < 0.1$

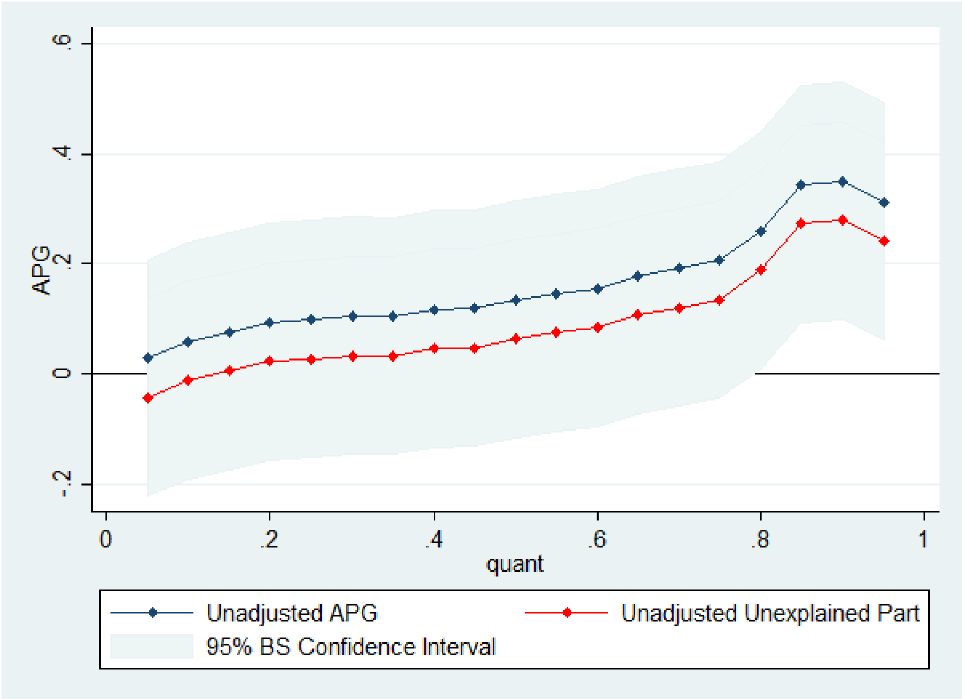

Figure 1: UQR estimates of the unadjusted APG and the corresponding unexplained part. Own calculations on Isfol Plus 2005-2016.

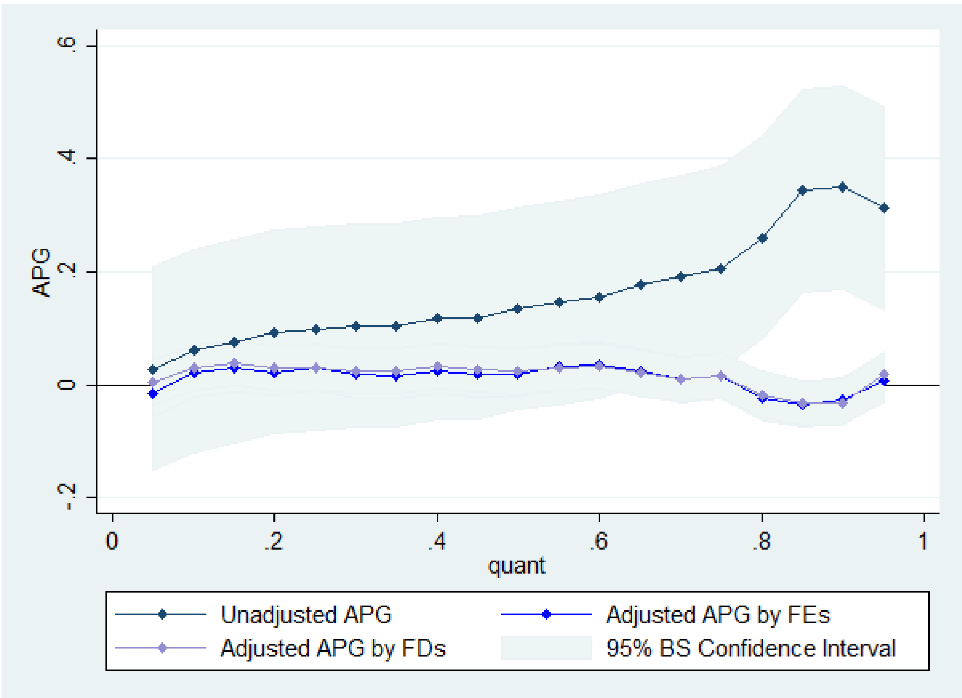

Figure 2: UQR estimates of the APG and the FEs adjusted gap. Own calculations on Isfol Plus 2005-2016.

distribution. In particular, the APG is highest at the upper part of the distribution. The unexplained part is insignificant at lower quantiles but relatively more pronounced at the upper part of the wage distribution. The APG at median and top quantiles cannot be explained by differences in labor market experience and job seniority. Adjustment of the APG by labor market heterogeneity allows to explain almost the entire gap. Only at the bottom of the wage distribution as well as at the mean (using first-differenced FEs), we find a remaining positive APG. That is only at the mean and bottom, we find evidence for favoritism of elder workers.

Summary statistics of the worker FEs by cohort and quantile show that the differences in the set of individual heterogeneity are small at the bottom but relatively large and significant at the top. A detailed decomposition reveals that the main part of the gap is due to heterogeneity at the individual level.

6 Robustness Test

In this Section, we repeat the analysis on different subsamples. First, we consider only male workers in public employment. Second, we consider female workers only, employed in both the public and the private sector. Finally, we consider the full sample. That is men and women in public and private employment in Italy.

Male Public Servants

In order to account for potential differences between the public and the private sector, the analysis is repeated for public-sector workers only. Indeed, the share of public servants is relatively high in Italy and automatic promotions based on age are particularly pronounced in public employment. In this sample, more than 61% of all male workers are public servants among the elderly cohort and 41% among the adult cohort (see Table 1, Panel B). In the sample not restricted to the largest connected set, we have 4,734 adult public servants and 8,438 adult private-sector workers (Table 2). This corresponds to 35.9% and 64.1%, respectively. For the elderly, we observe 4,134 (52.5%) public-sector workers and 3,736 (47.5%) private-sector workers. These numbers are in line with numbers of the OECD (2017) on public employment and pay in Italy. In Italy, a privatization process of public employment was launched aiming to make the public sector more efficient. During the last economic crisis, wage freezes and promotion stops were implemented in public employment. This may be important with regard to pay differences by age. We do not include women in this robustness check as the wage freeze affected women over-proportionately given that women are particularly prone to public employment in Italy (Piazzalunga and Di Tommaso, 2015).

Looking at the APG for public servants reveals again positive raw APGs throughout the wage distribution (see Figure 3). The gaps are particularly pronounced at the upper part of the distribution. However, the increase in the difference starts already at the 65th quantile. In the analysis of male private- and public-sector workers, the increase in the unadjusted gap starts only at the 80th quantile. In line with the results found for the sample of both public- and private-sector workers, the APG is increasing from the bottom to the top. The unexplained part is again a main driver of the raw gap.

The adjusted gap is again significantly reduced approaching zero. At the bottom it is positive, while it diverges from zero and becomes negative at the top. In both cases, the divergence from zero is more pronounced compared to the analysis in Section 5. This suggests that pay gaps corrected for labor market heterogeneity persist at the bottom. At the top, this result implies that the set of individual-specific characteristics is again higher for elder public servants compared to adult public workers. Table 5 shows that the differences in the set of individual FEs across the cohorts are always positive, except for low-income earners. Subtracting this positive set of covariates from the unadjusted APG explains the negative adjusted APG at upper points of the wage distribution.

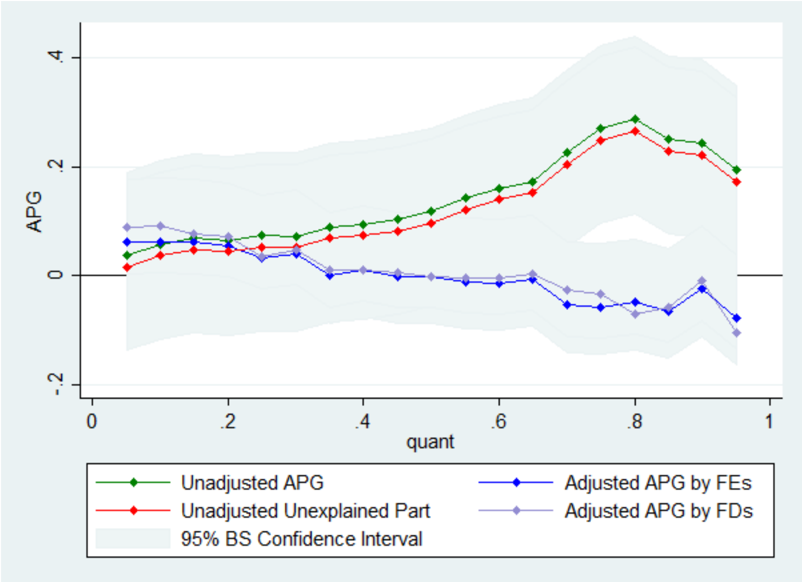

Figure 3: UQR estimates of the unadjusted and adjusted APG and the corresponding unexplained part for male public servants. Own calculations on Isfol Plus 2005-2016.

Table 5: Summary Statistics, Worker FEs – Male Public Servants

	(1)	(2)	(3)	(4)	(5)
	Elderly		Adult		
Quantile	Mean	Std.Dev.	Mean	Std.Dev.	Difference
Mean	0.115	0.377	-0.032	0.315	0.147
10	-0.009	0.280	0.008	0.333	-0.017
50	0.060	0.384	-0.053	0.376	0.113
90	0.151	0.733	-0.134	0.479	0.285
Observation	3,575		4,021		7,596

Notes: The Table shows the worker FEs that have been estimated using the partitioned procedure by Guimaraes and Portugal (2010) at different points of the wage distribution.

Female Employees

Due to larger employment gaps deriving from child-rearing and -bearing female workers are also considered separately. Labor market presence of women varies across the cohorts: 43% of all elderly workers are women, while 55% of all adult workers are female. This is in line with increasing labor market participation of women over time (Godin, 2014). The general trend of increasing APGs from the bottom to the top is confirmed also for the female subsample (see Figure 4). However, the APG at lower quantiles as well as at the median and mean is much more pronounced. The unexplained part is again a main driver of the gap of middle- and top-income earners.

The APG is adjusted towards zero in the full model. Also for women, higher sets of individual labor market heterogeneity (both observable and unobservable) of elder female workers allow to explain almost the entire APG between female workers. The difference in worker FEs in favor of elder women is much more pronounced at the 90th quantile compared to the 10th or 50th (see Table 6). A major difference compared to the case of male workers is that the adjusted wage gaps between elder and adult women is not positive at the bottom. That is higher sets of individual heterogeneity of elder women correct the APG to zero (or even slightly below) also at the bottom of the wage distribution.

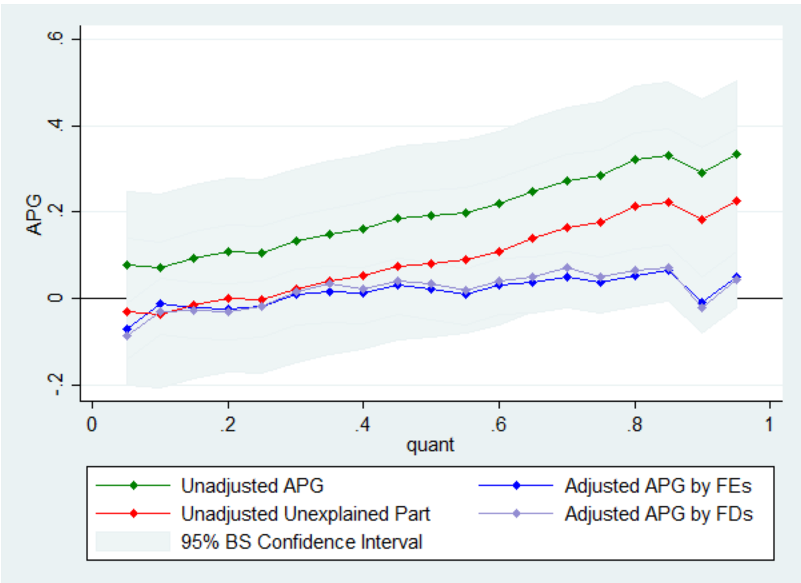

Figure 4: UQR estimates of the unadjusted and adjusted APG and the corresponding unexplained part for women. Own calculations on Isfol Plus 2005-2016.

Table 6: Summary Statistics, Worker FEs – Women

	(1)	(2)	(3)	(4)	(5)
	Elderly		Adult		
Quantile	Mean	Std.Dev.	Mean	Std.Dev.	Difference
Mean	0.219	0.401	0.037	0.344	0.182
10	0.067	0.311	-0.026	0.377	0.093
50	0.117	0.410	-0.045	0.412	0.162
90	0.233	0.909	-0.090	0.59	0.323
Observation	4,908		12,712		17,620

Notes: The Table shows the worker FEs that have been estimated using the partitioned procedure by Guimaraes and Portugal (2010) at different points of the wage distribution.

Full Sample

Finally, we run the estimation on the full sample including both men and women as well as the public and the private sector. Figure 5 shows again higher APGs at the top and lower gaps at the bottom of the distribution. Adjusting for labor market heterogeneity corrects the gap towards zero at all points of the wage distribution. Table 7 shows that the set of individual worker FEs is again higher for the elder cohort compared to the adult cohort.

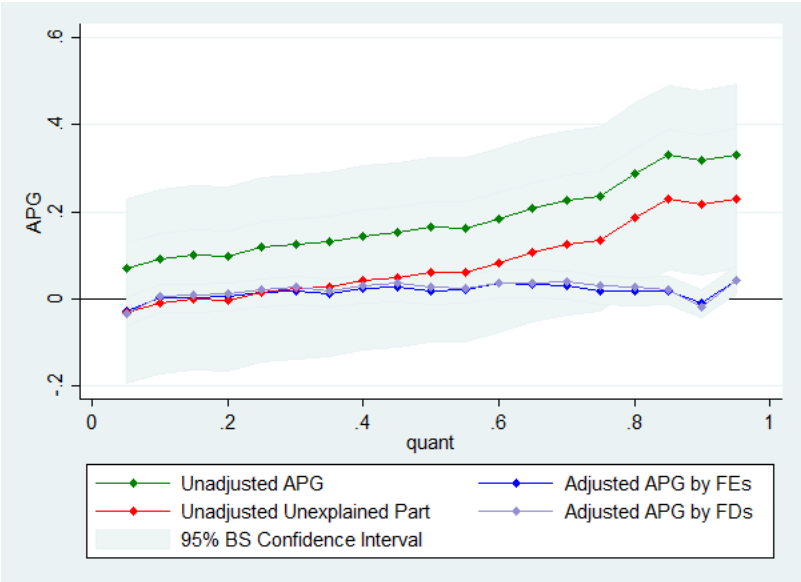

Figure 5: UQR estimates of the unadjusted and adjusted APG and the corresponding unexplained part for the full sample. Own calculations on Isfol Plus 2005-2016.

Table 7: Summary Statistics, Worker FEs – Full Sample

	(1)	(2)	(3)	(4)	(5)
	Elderly		Adult		
Quantile	Mean	Std.Dev.	Mean	Std.Dev.	Difference
Mean	0.219	0.391	0.045	0.335	0.174
10	0.061	0.342	-0.029	0.424	0.091
50	0.095	0.372	-0.045	0.378	0.140
90	0.230	0.994	-0.109	0.659	0.339
Observation	10,943		23,117		34,060

Notes: The Table shows the worker FEs that have been estimated using the partitioned procedure by Guimaraes and Portugal (2010) at different points of the wage distribution.

All in all, we find positive APGs along the wage distribution. Adult workers seem to be particularly punished for lower sets of individual worker FEs. Two main differences for the female subsample emerge. First, the APG is larger for women. Second, we find no evidence for favoritism at the bottom (as the FEs- and FDs-adjusted APGs are not positive at the bottom). The general pattern of increasing APGs at upper quantiles and substantial reductions in the gap when adjusted for FEs persists. Another important pattern that is robust to different samples is that the unexplained part is a main driver of the gap at upper quantiles but negligible at the bottom. Consequently, automatic promotions based on age and job seniority cannot explain the APG for middle- and high-income earners in Italy. In contrast, the pay gap at the bottom is entirely explained by these characteristics.

7 Conclusion

This paper calculates the Age Pay Gap (APG) in Italy by accounting for differences in labor market heterogeneity that are generally unobserved using standard estimation techniques. The individual set of characteristics taken into account contains general individual characteristics like schooling as well as generally unobserved motivation and commitment to work. This set is found to be higher for elder (55-64) compared to adult (34-54) workers. According to a large part of the literature the age-productivity profile is decreasing over the life-cycle (Lazear, 1979; Cardoso et al., 2011). This study adds to the literature on APGs by finding that decreasing productivity profiles by age can be outweighed by other, generally unobserved, characteristics at the individual-level. This has been ignored by the literature so far. Another point that has been neglected by the literature are changes of the wage gap along the distribution. The APG in the last decade in Italy is driven by differences in labor market experience and job tenure at the bottom but remains mainly unexplained by these characteristics at middle and upper quantiles.

We adjust the APG for individual, industry and job FEs that are calculated using an iterative procedure. The corrected gap is substantially lower at all points of the wage distribution. This result holds also when it is accounted for potential endogeneity of job and industry changes using first differences. Using unconditional quantile regressions revealed that there are substantial differences in the pay gap between cohorts along the wage distribution. The most pronounced wage gaps are found at the top. At upper quantiles, the differences in the set of worker heterogeneity was also found to be most pronounced. The gap is driven by individual labor market heterogeneity and therefore, this set of personal characteristics, plays a crucial role for the existence of pay differences across cohorts. This holds for all points of the wage distribution. The analysis does not find evidence for favoritism of elder workers in pay at the mean and top.

The main findings are robust to various subsamples. However, the APGs for women are relatively larger. In the public sector, the wage gap based on differences in labor market heterogeneity for the lower part of the wage distribution is particularly pronounced. The APG for the female subsample is relatively larger at the bottom and middle of the wage distribution. Labor market experience and seniority are important in explaining the APG at the bottom. The APG is especially large at the top and correcting for labor market heterogeneity adjusts the gap substantially downwards.

To the author's best knowledge the underlying study is the first application estimating the APG in Italy while accounting for the role of workers' labor market heterogeneity. The method applied allows to explain the APG almost completely, underlining the importance to account for different sources of heterogeneity (worker, job and industry) when it comes to differences in pay by age. Moreover, this study shows that it is important to consider differences in the pay gap along the wage distribution. Adjusting the APG for individual heterogeneity and job and industry sorting reduces the gap at the median and top of the wage distribution to zero. At the bottom, the differential is small but statistically significant. These results do not confirm the public perception that elder individuals are favored in Italy. We find no evidence of overpayment of elder and underpayment of adult workers, once we account for generally unobserved labor market heterogeneity.

References

Addison, J. T., P. Teixeira, J. Stephani, and L. Bellmann (2015): "Declining Unions and the Coverage Wage Gap: Can German Unions Still Cut It?" *Journal of Labor Research*, 36 (3), 301–317.

Antonczyk, D., B. Fitzenberger, and K. Sommerfeld (2010): "Rising wage inequality, the decline of collective bargaining, and the gender wage gap," *Labour Economics*, 17, 835–847.

Aubert, P. and B. Crépon (2003): "La productivité des salariés âgés: une tentative d'estimation," *Économie et statistique*, 368, 95–119.

Autor, D. H., L. F. Katz, and M. S. Kearney (2008): "Trends in US wage inequality: Revising the revisionists," *The Review of Economics and Statistics*, 90, 300–323.

Avolio, B. J. and D. A. Waldman (1994): "Variations in cognitive, perceptual, and psychomotor abilities across the working life span: Examining the effects of race, sex, experience, education, and occupational type." *Psychology and Aging*, 9, 430.

Becker, G. S. (2010): *The Economics of Discrimination*, Chicago: University of Chicago Press, 2 ed.

Blinder, A. (1973): "Wage Discrimination: Reduced Form and Structural Estimates," *Journal of Human Resources*, 8, 436–455.

Bordogna, L. and S. Neri (2012): "Social dialogue and the public services in the aftermath of the economic crisis: strengthening partnership in an era of austerity in Italy: National report," Tech. rep., King's College London.

Brandolini, A. (2005): "La disuguaglianza di reddito in Italia nell'ultimo decennio," *Stato e mercato*, 74, 207–229.

Cardoso, A. R., P. Guimarães, and J. Varejão (2011): "Are older workers worthy of their pay? An empirical investigation of age-productivity and age-wage nexuses," *De Economist*, 159, 95–111.

Cardoso, A. R., P. Guimarães, and P. Portugal (2016): "What Drives the Gender Wage Gap? A Look at the Role of Firm and Job-Title Heterogeneity," *Oxford Economic Papers*, 68, 506–524.

Chen, Y. and S. X. Li (2009): "Group identity and social preferences," *American Economic Review*, 99, 431–57.

Contini, B. and U. Trivellato (2005): *Eppur si muove. Dinamiche e persistenze nel mercato del lavoro italiano*, Milano: Società editrice il Mulino.

Corsetti, G. and E. Mandrone (2012): *ISFOL PLUS Survey, in Labour Economics: Plus Empirical Studies, Temi and Ricerche ISFOL*, Ediguida.

Crepaldi, C., F. Pesce, and M. S. Lodovici (2014): "The Social and Employment Situation in Italy," Tech. rep., European Parliament, accessed: 2018-06-09.

de Hek, P. and D. van Vuuren (2011): "Are older workers overpaid? A literature review," *International Tax and Public Finance*, 18, 436–460.

DiNardo, J., N. M. Fortin, and T. Lemieux (1996): "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach," *Econometrica*, 64, 1001–44.

Disney, R. (2000): "Crises in public pension programmes in OECD: What are the reform options?" *The Economic Journal*, 110, 1–23.

Firpo, S., N. M. Fortin, and T. Lemieux (2009): "Unconditional Quantile Regressions," *Econometrica*, 77, 953–973.

Fortin, N., T. Lemieux, and S. Firpo (2011): *Decomposition Methods in Economics*, Elsevier, vol. 4 of *Handbook of Labor Economics*, chap. 1, 1–102.

Galenson, D. W. and B. A. Weinberg (2000): "Age and the quality of work: The case of modern American painters," *Journal of Political Economy*, 108, 761–777.

Gaure, S. (2010): "OLS with Multiple High Dimensional Category Dummies," Tech. rep.

Godin, C. (2014): "A Grand Gender Convergence: Its Last Chapter," *American Economic Review*, 104, 1091–1119.

Guimaraes, P. and P. Portugal (2010): "A Simple Feasible Alternative Procedure to Estimate Models with High-Dimensional Fixed Effects," *Stata Journal*, 10, 628–649.

Huck, S., A. J. Seltzer, and B. Wallace (2011): "Deferred compensation in multiperiod labor contracts: an experimental test of Lazear's model," *American Economic Review*, 101, 819–43.

Jann, B. (2008): "The Blinder-Oaxaca Decomposition for Linear Regression Models," *The Stata Journal*, 8, 453–479.

Lazear, E. (1979): "Why Is There Mandatory Retirement?" *Journal of Political Economy*, 87 (6), 1261–1284.

——— (1981): "Agency, earnings profiles, productivity, and hours restrictions," *The American Economic Review*, 71, 606–620.

Loewenstein, G. and N. Sicherman (1991): "Do workers prefer increasing wage profiles?" *Journal of Labor Economics*, 9, 67–84.

Machado, J. A. F. and J. Mata (2005): "Counterfactual Decomposition of Changes in Wage Distributions using Quantile Regression," *Journal of Applied Econometrics*, 20, 445–465.

Martins, P. S. and P. T. Pereira (2004): "Does education reduce wage inequality? Quantile regression evidence from 16 countries," *Labour Economics*, 11, 355–371.

Massimiliano, B., F. Tommaso, S. Francesco, et al. (2017): "Grandparental availability for child care and maternal labor force participation: Pension reform evidence from Italy," *Journal of Population Economics*, 1–39.

Mc Dermott, R. (2009): *Psychological approaches to identity: Experimentation and application*, Cambridge University Press, vol. 1 of *Measuring Identity: A Guide for Social Scientists*, chap. 12, 345–368.

McCue, K. (1996): "Promotions and Wage Growth," *Journal of Labor Economics*, 14, 175–209.

Milgrom, P. and J. Roberts (1988): "An economic approach to influence activities in organizations," *American Journal of Sociology*, 94, S154–S179.

Neumark, D. (1988): "Employers' Discriminatory Behavior and the Estimation of Wage Discrimination," *Journal of Human Resources*, 23, 279–295.

Oaxaca, R. (1973): "Male-Female Wage Differentials in Urban Labor Markets," *International Economic Review*, 14, 693–709.

OECD (2004): "OECD Employment Outlook, Chapter 3, Wage Setting Institutions and Outcomes," `https://www.oecd.org/employment/emp/34846881.pdf`.

——— (2013): *Pensions at a Glance 20133: OECD and G20 Indicators*, OECD Publishing.

——— (2016): "OECD Factbook 2016: Economic, Environmental and Social Statistics," .

——— (2017): "Government at a Glance – Italy," `https://www.oecd.org/gov/gov-at-a-glance-2017-italy.pdf`.

Pencavel, J. (1991): *Labor Markets under Trade Unionism: Employment, Wages, and Hours*, Blackwell.

Piazzalunga, D. and M. L. Di Tommaso (2015): "The Increase of the Gender Wage Gap in Italy during the 2008-2012 Economic Crisis," .

Prendergast, C. and R. H. Topel (1996): "Favoritism in organizations," *Journal of Political Economy*, 104, 958–978.

Regan, T. L. and R. L. Oaxaca (2009): "Work experience as a source of specification error in earnings models: implications for gender wage decompositions," *Journal of Population Economics*, 22, 463–499.

Rosolia, A. and R. Torrini (2007): "The generation gap: relative earnings of young and old workers in Italy," Tech. Rep. 639, Banca d'Italia.

Russo, C. (2007): *Il ruolo del sindacato nella riforma del lavoro pubblico*, Dell'Aringa-Della Rocca, op. cit, 167–201.

Skirbekk, V. (2004): "Age and Individual Productivity: A Literature Survey," *Vienna Yearbook of Population Research*, 133–153.

Walker, I. and Y. Zhu (2003): "Education, earnings and productivity: recent UK evidence," *Labour Market Trends*, 111, 145–152.

Weeks, D. L. and D. R. Williams (1964): "A Note on the Determination of Connectedness in an N-Way Cross Classification," *Technometrics*, 6.

Appendix

Table A.1: Definition of Variables

Variable Name	Definition
	Dependent Variables
Lhwage	The natural log of net hourly wages; hourly wages in Euros, net of taxes and social security contributions
	Independent Variables
	Group Identifier
adult	Dummy: one if the respective individual is aged between 34-54 years, zero if the respective individual is aged between 55-64 years
	Labor Market Presence
Exper	Number of years of prior work experience defined as: *Year - Year started working*
Exper2	Exper squared
Tenure	Number of years worked for current employer
	Educational Attainment
Educ_1	One if individual's highest degree is elementary school, zero otherwise
Educ_2	Dummy: one if individual's highest degree is middle school ('medie inferiori'), zero otherwise
Educ_3	Dummy: one if individual's highest degree is 'diploma', zero otherwise
Educ_4	Dummy: one if individual graduated from university, zero otherwise
North	Dummy: one if individual lives and works in the North of Italy, zero otherwise
Centre	Dummy: one if individual lives and works in the Centre of Italy, zero otherwise
Italian	Dummy: one if individual holds the Italian citizenship, zero otherwise
Married	Dummy: one if married, zero otherwise
	Occupations and Industries
Jobs	Occupational dummies: Managers, Entrepreneurs and Legislators; Professional, Intellectual and Scientific; Technical; White-Collar; Teacher; Craftsmen and Highly-specialized; Semi-qualified Non-qualified Occupations, Armed Forces
Industries	Sectoral dummies: Agriculture; Industry; Energy; Construction; Commerce; Tourism; Transport; Communication; Financial Activity; Services for Firms; Public Administration; Education; Health; Professional and Scientific Sector; Family Services; International Sector
Public_Sec	Dummy: one if firm is a publicly owned firm, zero otherwise

Fixed Effects

Individual_FEs	Worker FEs
Job_FEs	Job FEs
Industry_FEs	Industry FEs
Year dummies or Year FEs	Dummy: one if the data was collected in either 2005, 2006, 2008, 2010, 2011, 2014 or 2016,

Table A.2: Regression Log Net Hourly Wages with FEs at the Mean

	(1)	(2)
	Full Model	Full Model
Variables	Lhwage	Lhwage
adult	0.013	0.013***
	(0.012)	(0.004)
FE1		1.000***
		(0.002)
FE2		1.000***
		(0.074)
FE3		1.000***
		(0.162)
Constant	2.346***	2.341***
	(0.078)	(0.010)
Year FEs	Yes	Yes
Worker, job and industry FEs	Yes	Yes
Observations	16,440	16,440
R-squared	0.026	0.690

Robust Standard errors in parentheses
Standard errors clustered at the individual level
$***p < 0.01, **p < 0.05, *p < 0.1$

Notes: The model in column (1) was estimated as a FEs model with three sets of dummy variables as regressors (time, job and industry). The model in column (2) contains FEs (individual, job and industry) estimated with the partitioned iterative procedure proposed by Guimaraes and Portugal (2010).

In der Diskussionspapierreihe sind kürzlich erschienen:

Recently published Discussion Papers:

105	Töpfer, M.	The Age Pay Gap and Labor Market Heterogeneity: A New Empirical Approach Using Data for Italy	07/2018
104	Fackler, D., Fuchs, M., Hölscher, L., Schnabel C.	Do startups provide employment opportunities for disadvantaged workers?	05/2018
103	Castagnetti, C., Rosti, L., Töpfer, M.	Discriminate Me – if You Can! The Disappearance of the Gender Pay Gap among Public-Contest Selected Employees	02/2018
102	Oberfichtner, M., Schnabel, C.	The German Model of Industrial Relations: (Where) Does it still Exist?	10/2017
101	Lechmann, D.	Estimating labor supply in self-employment: pitfalls and resolutions	09/2017
100	Kuehnle, D. Oberfichtner, M.	Does early child care attendance influence children's cognitive and non-cognitive skill development?	03/2017
99	Hinz, T.	Personnel policy adjustments when apprentice positions are unfilled: Evidence from German establishment data	09/2016
98	Lechmann, D., Wunder, C.	The dynamics of solo self-employment: persistence and transition to employership	05/2016
97	Hirsch, B., Jahn, E. J., Oberfichtner, M.	The urban wage premium in imperfect labour markets	01/2016
96	Hirsch, B., Lechmann, D., Schnabel, C.	Coming to work while sick: An economic theory of presenteeism with an application to German data	04/2015
95	Schnabel, C.	United, yet apart? A note on persistent labour market differences between western and eastern Germany	03/2015

Eine aktualisierte Liste der Diskussionspapiere findet sich auf der Homepage:
http://www.arbeitsmarkt.rw.fau.de/

An updated list of discussion papers can be found at the homepage:
http://www.arbeitsmarkt.rw.fau.de