The Age Pay Gap in Italy
– Investigating the Sources of the Pay Differential by Age – *

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Abstract

Using Italian microdata over the period 2005-2014, the paper studies the difference in pay between elderly and adult workers in Italy. For this purpose, the role of job-title, industry- and individual-specific heterogeneity in explaining the age-related pay disparity is examined. The estimation strategy consists in using the Gelbach decomposition of the conditional wage gap combined with a four-way fixed effects wage model. The FEs of interest (individual, job and industry) are estimated via a partitioned procedure. The model allows to explain the entire (conditional) age pay gap. The results suggest that individual heterogeneity is the main driver of the (conditional) age pay gap. Industry-sorting contributes statistically significantly to the pay gap, while job-sorting is found to be insignificant.

Keywords: Age Pay Gap, Four-Way Fixed Effects Model, Gelbach Decomposition.

JEL - Classification: J7, J14, J310

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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 (Carneiro et al., 2011). Generally, wages increase with labor market experience and therefore age, i.e. there are positive and significant differences in pay between elder and adult labor market participants. Recently, research has focused on differences in productivity between elder and adult workers in order to find a justification of the elders' relative higher wages (for an overview see Carneiro et al., 2011). The findings suggest that the decline in average productivity starts approximately at the age of 50 (Skirbekk, 2004; Carneiro et al., 2011). The wage increase with age is thereby often found to outnumber the relative better productivity profile of the elder. Hence, it is of particular interest to gain additional insights on what actually drives the pay gap. Three main – in standard estimation techniques unobserved – factors play a role; worker, industrial and job heterogeneity. Individual productivity depends on the individual's ability as well as on his or her educational background and labor market experience. 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. In this study, these three sources of permanent labor market heterogeneity are taken into account when estimating the Age Pay Gap (APG) conditional on experience, tenure and time effects.

The underlying study considers the case of Italy. Similarly to Northern European countries like Finland or Sweden, collective bargaining power is relatively high in Italy. According to the literature, unionism contributes to higher wage levels and job stability as well as to automatic mechanisms of wage progression (Pencavel, 1991). Moreover, early retirement has been used as an instrument to solve economic crises in the last decade in Italy. However, the resulting immense fiscal burden as well as potential skill gaps in the workforce contributed to a re-thinking of this strategy (Disney, 2000). In the 'Europe 2020 Growth Strategy' of the European Union, the member states are encouraged to promote labor market participation of women, younger and older workers (European Commission, 2010). All of these factors (degree of unionism in a country, national retirement strategies, promotion of specific groups in the labor market) influence the presence as well as the wage level of elder and adult workers differently and therefore may result in pay disparities that are not merit-based.

As already mentioned, on average wages increase with age leading to significant differences in pay between elder and adult employees. However, even after controlling for experience, tenure and time Fixed Effects (FEs), there remains a substantial (conditional) pay gap across generations. The inclusion of worker, job and industry FEs allows to account for otherwise unobserved permanent heterogeneity. The estimation strategy consists in estimating FEs of generally unobserved heterogeneity by partitioning the estimation of the regression in different sets of equations and solving each equation separately (Gaure, 2010; Guimaraes & Portugal, 2010). The decomposition analysis is based on the Omitted Variable Bias (OVB) formula proposed by Gelbach (2016), where the omitted variables are three additional FEs. Using the Gelbach decomposition of the conditional pay gap obtained from a wage equation with FEs, the conditional APG can be explained completely. In particular, workers' permanent heterogeneity accounts for almost 100% of the pay differential. Job-level sorting is found to have no impact on the APG, while sector differences across generations explain about 1% of the conditional wage gap.

The contribution of the paper is two-fold. First, the applied estimation strategy catches otherwise unobserved heterogeneity at the worker-, job- and industry-level. Thereby, the APG in Italy can be explained entirely. Second, to the author's best knowledge, this study is the first application of the method described in Section 3 to the case of Italy and the APG in general.

This paper is organized as follows. In Section 2 the data is described. Next, the estimation strategy and the results obtained are presented in Section 3 and 4, respectively. In Section 5, we run a robustness checks on a subsample with a presumably lower apriori degree of individual heterogeneity, i.e. we consider only university graduates. Section 6 concludes.

2 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). In the investigation, the complete release of panel dimension is used, i.e. data over the period 2005-2014. We keep full-time employees aged 34-64 years. This gives a total sample size of 28,101 observations. The sample is then restricted to the largest connected set (identified via the algorithm proposed by Weeks & Williams, 1964), what leaves us with 24,793 positive wage observations. In the sample, 8,240 individuals belong to the group aged 55-64 years and 16,553 individuals to the group aged 34-54 years. Individuals aged below 55 years are labeled 'adult', while all individuals above that threshold are considered to be part of the 'elderly' group.

We do not have linked employer-employee data and hence do not have information on the employer side (e.g. firm FEs). Similarly, the job categories and industrial classification are not as narrowly defined as it is generally the case with linked employer-employee data. We observe nine different industries and 144 industry-job classifications. 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.

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. In Tables A.2-A4, descriptive statistics of worker, job and industry FEs are provided. These FEs are estimated via the iterative procedure proposed by Guimaraes and Portugal (2010). A substantial raw APG amounting to 19.0 percentage points is found in the underlying sample for Italy. Elder and adult employees are relatively equal in terms of educational attainment; on average an individual in the sample has enjoyed 13 years of education. As expected labor market experience and job tenure are higher for the elderly. The average age of the elder workers lies above the threshold of declining productivity (age of 50), while that of the adult cohort lies almost half a decade below this benchmark. The adult subsample contains more than twice as much observations as 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 from the fact that the effective age of labor market exit in Italy is the fourth lowest within the OECD (OECD, 2013).

Table 1: Descriptive Statistics

	(1)	(2)	(3)	(4)
	Elderly		Adult	
	Mean	Std.Dev.	Mean	Std.Dev.
Lhwage	2.376	0.458	2.190	0.407
Schooling (years)	13.27	2.886	12.82	2.839
Exper	34.62	5.898	24.58	8.496
Tenure	27.21	9.928	17.79	9.844
Age	57.66	2.311	46.24	6.389
Observations	8,240		16,553	

3 Estimation Strategy

The estimation strategy consists in estimating a linear model with FEs following Guimaraes and Portugal (2010) and Gaure (2010). This procedure allows to identify the point estimates of the FEs without having to invert the matrices but by using an iterative procedure. For identification 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 start by estimating the following Mincer-type base equation:

$$
\begin{aligned}
y_{it} &= x_{it}\beta^{base} + \delta_t + \epsilon_{it}^{base} \\
y_{it} &= \alpha_0 + a_{it}\beta_1^{base} + \tilde{x}_{it}\tilde{\beta}^{base} + \delta_t + \epsilon_{it}^{base}
\end{aligned}
\tag{1}
$$

with $x_{it} \equiv [1, a_{it}, \tilde{x}_{it}]$ having dimension $(1 \times 1+1+K-2)$, i.e. $1 \times K$ and $\beta^{base} = [\alpha_0^{base}, \beta_1^{base}, \tilde{\beta}^{base}]$ having dimension $K \times 1$. The constant is represented by α_0, a_{it} is a dummy that identifies the cohort or generation the individual belongs to, i.e. either 'Adult' or 'Elderly'. This variable is pivotal for the analysis as it provides the (conditional) APG. The vector of regressors $\tilde{x}_{it}$ contains $K-2$ explanatory variables. The explanatory variables included are experience and tenure as well as their squares, δ_t contains time dummies. The error 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 $(t = 1 \dots T)$.

Next, we add the following FEs to the base model

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

$$
\begin{aligned}
y_{it} &= x_{it}\beta^{full} + \delta_t + \epsilon_{it}^{full} \\
y_{it} &= \alpha_0 + a_{it}\beta_1^{full} + \tilde{x}_{it}\tilde{\beta}^{full} + \delta_t + \psi_i + \phi_j + \lambda_d + \epsilon_{it}^{full}
\end{aligned}
\tag{2}
$$

where ψ_i, ϕ_j and λ_d are the FEs that have been omitted in the base model (1). The vector $\beta^{full} = [\alpha_0^{full}, \beta_1^{full}, \tilde{\beta}^{full}]$ has again dimension $K \times 1$. In matrix notation, the model has the following form:

$$
Y = X\beta + G\delta + E\psi + J\phi + D\lambda + \epsilon \tag{3}
$$

where Y is the $N^* \times 1$ vertically stacked vector of wages sorted by i, t, d, j and $N^* = K+N+J+D$. 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 additional 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. Even though the standard estimation approach is feasible here ($N^* \approx 25,000$), the algorithm applied offers a convenient way to estimate the FEs. 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.[1]

Decomposition

The Gelbach (2016) decomposition allows us to estimate the change in the coefficient estimate of the age dummy a, $\hat{\beta}_1^{base} - \hat{\beta}_1^{full}$, when we go from the base model (1) to the full model (2). Any changes in the coefficient estimates of β_1^{base} compared to β_1^{full} will be due to individual heterogeneity as well as sorting in jobs or industries other things equal. The Gelbach decomposition uses the OVB formula allowing to attribute to each covariate in the full model a component contributing to β_1^{base}. The set of FEs (ϕ, ψ, λ), is thereby considered as the set of omitted variables:

$$\begin{aligned}\hat{\beta}^{base} - \hat{\beta}^{full} &= (a^{'}a)^{-1}a^{'}E\hat{\psi} + (a^{'}a)^{-1}a^{'}J\hat{\phi} + (a^{'}a)^{-1}a^{'}D\hat{\lambda} \\ &= \hat{\theta}_{\psi} + \hat{\theta}_{\phi} + \hat{\theta}_{\lambda} \end{aligned} \tag{4}$$

where each $\hat{\theta}$ represents the log point reduction in the APG that would occur if elderly and adult workers were equally paid across the category of the specific FE. The interpretation of $\hat{\theta}$ is conducted conditional on all other variables included in the full model.

As we are interested in the contribution of different sources of heterogeneity at the individual, job- and industry-level and $T < 10$, we use in the decomposition estimates of the three FEs, $\hat{psi}$, $\hat{\phi}$ and $\hat{\lambda}$, obtained with the partitioned procedure. In contrast, the year FEs enter the decomposition equation as a set of time dummies.

If we are interested in the raw APG, the cohort dummy a is the only regressor in the base specification. However, the raw APG ignores time-varying effects that may contribute to the APG. Moreover, higher levels of labor market experience and job tenure are driven by age. In order to obtain a pay gap between observational identical individuals, the APG is estimated conditional on experience, tenure and timed.

4 Estimation Results

The raw APG amounts to 19 percentage points throughout Italy in the period 2005-2014 (see Table 2). The adjusted APG conditional on workers' experience and tenure increases slightly to 21 percentage points reflecting, compared to the elderly, the adults' (34-55) natural disadvantage in those attributes.This conditional APG constitutes an average differential between the wages of two otherwise observably identical workers in terms of experience and firm seniority. Column (3) shows the regression outcome from the full model that includes worker, job and industry FEs as well as time-varying characteristics such as experience, job tenure and time FEs. The APG that remains unexplained by worker, job or industry heterogeneity drops to 0.7 percentage points. This implies that the additional regressors, i.e. the three FEs, explain 97% of the gap.

[1]See Table A.5 for an application.

Table 3 represents the results of the decomposition. We explain the APG by accounting for different sources of heterogeneity; individual-specific heterogeneity as well as job- and industry-related segregation. Allocation in jobs does not contribute to the pay differential between the two cohorts. Sorting in different industries accounts for approximately 1% of the conditional APG (or 0.2 log points). Worker FEs absorb all time-invariant individual-specific characteristics such as educational differences. Differences in the individual FEs by age group contribute to 21 log points of the conditional APG. That is they explain the entire gap of 21 percentage points. Hence, individual-specific heterogeneity persists within industries and jobs for workers with the same amount of experience and firm seniority. Worker FEs can be a proxy for productivity, i.e. catch individual ability, but also reflect favoritism that is not associated with sorting of workers in a specific job and industry. If one assumes that adult and elderly workers employed in the same industry and doing the same job have equal ability or productivity, this part of the gap can be referred to as 'favoritism' of older workers and reveals that differences in job and industry FEs do not contribute substantially to the (conditional) APG. In this sense, elderly workers obtain a premium compared to adult workers based on their group characteristics.

The results of the decomposition analysis suggest that individual heterogeneity is the most important source of variation. Using a four-way FEs model allows us to catch otherwise unobserved heterogeneity. Moreover, the estimation strategy applied explains (almost) the entire conditional APG.

Table 2: Regressions Log Net Hourly Wages

	(1)	(2)	(3)
	Raw APG	Base Model	Full Model
Variables	Lhwage	Lhwage	Lhwage
young	-0.186***	-0.207***	0.007*
	(0.028)	(0.037)	(0.004)
Tenure		0.006**	0.001***
		(0.002)	(0.000)
Tenure2		0.000	-0.000***
		(0.000)	(0.000)
Exper		0.027***	-0.000
		(0.003)	(0.001)
Exper2		-0.001***	0.000**
		(0.000)	(0.000)
Constant	2.376***	2.014***	2.123***
	(0.070)	(0.103)	(0.010)
Year FEs	No	Yes	Yes
Worker, job and industry FEs	No	No	Yes
Observations	24,793	24,793	24,793

Standard Errors clustered at the job level.
$***p < 0.01, **p < 0.05, *p < 0.1$

Table 3: Gelbach Decomposition

	(1)
Variables	Lhwage
Individual_FE ($\hat{\theta}_\psi$)	-0.211***
	(0.006)
Job_FE ($\hat{\theta}_\phi$)	-0.000
	(0.000)
Industry_FE ($\hat{\theta}_\lambda$)	-0.002***
	(0.000)
Total ($=\hat{\theta}_\psi + \hat{\theta}_\phi + \hat{\theta}_\lambda$)	-0.213***
	(0.006)
Observations	24,793

Standard Errors clustered at the job level.
$***p < 0.01, **p < 0.05, *p < 0.1$

5 Robustness Test

In order to double check the result obtained in Section 4 finding that worker heterogeneity is the main driver of the APG, the analysis is repeated on a subsample among which the degree of heterogeneity is lower compared to the full sample. We restrict the sample to university graduates.

The restriction of the sample to employees holding a university degree is expected to reinforce the assumption that adult and elderly workers employed in the same industry and doing the same job have equal ability or productivity. Hence, by this restriction, the level of heterogeneity in the sample is assumed to be decreased. About one third of the original sample are university graduates. The raw APG is higher for this subsample amounting to more than 23 percentage points. However, the conditional APG is much lower amounting to 9 percentage points (see Table 4). In the full model, the part unexplained by heterogeneity at the individual-, job- or industry level vanishes. The decomposition in Table 5 shows that the gap is entirely explained by worker FEs. As in this subsample differences in productivity – other things equal – should be less pronounced, the driver of positive differences between elder and younger workers may be favoritism of elder employees (over adult employees). Consequently, differences in pay by age may not be merit-based.

Table 4: Regressions Log Net Hourly Wages, Graduates

	(1)	(2)	(3)
	Raw APG	Base Model	Full Model
Variables	Lhwage	Lhwage	Lhwage
young	-0.233***	-0.094***	0.006
	(0.016)	(0.016)	(0.007)
Tenure		-0.003*	-0.006***
		(0.002)	(0.002)
Tenure2		0.000**	0.000***
		(0.000)	(0.000)
Exper		0.030***	0.001
		(0.003)	(0.002)
Exper2		-0.000***	-0.000***
		(0.000)	(0.000)
Constant	2.663***	2.106***	2.544***
	(0.042)	(0.080)	(0.022)
Year FEs	No	Yes	Yes
Worker, job and industry FEs	No	No	Yes
Observations	7,794	7,794	7,794

Standard Errors clustered at the job level.
$***p < 0.01, **p < 0.05, *p < 0.1$

Table 5: Gelbach Decomposition, University Graduates

	(1)
Variables	Lhwage
Individual_FE ($\hat{\theta_\psi}$)	-0.102***
	(0.011)
Job_FE ($\hat{\theta}_\phi$)	-0.001
	(0.003)
Industry_FE ($\hat{\theta}_\lambda$)	0.003
	(0.003)
Total ($=\hat{\theta}_\psi + \hat{\theta}_\phi + \hat{\theta}_\lambda$)	-0.100***
	(0.011)
Observations	7,794

Standard Errors clustered at the job level.
$***p < 0.01, **p < 0.05, *p < 0.1$

6 Conclusion

This paper identifies sources of the pay differential between generations accounting for age-related differences in experience and tenure. By applying the Gelbach decomposition with a four-way FEs wage model, the entire (conditional) APG can be explained. The APG is estimated conditional on experience and firm seniority as these variables can be considered as the natural advantage of the elderly over adult labor market participants. Individual heterogeneity was found to be the most important driver of the disparity in pay between elderly and adult workers. As it accounts for workers being occupied in the same job category and the same industry, holding experience and tenure fixed, these workers can be assumed to have similar levels of productivity (Cardoso et al., 2016). Therefore, this part of the APG can be referred to as favoritism of elder workers. Heterogeneity at the industry-level has only a small impact on the gap (approximately 1%), while job-sorting does not explain differences in pay across generations. Differences in individual heterogeneity are the main driver, even when the level of differences in productivity in the sample is decreased (restricting the sample to university graduates). For workers with tertiary education, permanent heterogeneity is the only significant driver of the conditional APG. In contrast, differences in job-sorting behavior by generation as well as industry-sorting do not significantly contribute to the pay gap.

In the past, early retirement was used as an instrument to resolve economic crises in Italy (Disney, 2000), what led to a relative low share of elder workers in the Italian labor market compared to other OECD countries (OECD, 2013). This technique has also made the Italian pension system one of the most expensive and thereby increased the burden on the younger generations to prevent the social security and pension system from collapsing. Hence, it is important to study the drivers of differences in pay by age group. Industry-related heterogeneity plays a minor role in determining the gap; 0.2 log points of the gap can be attributed to industries' permanent heterogeneity, while job-title heterogeneity was found to have no impact. This result might be driven by strong unions in Italy. Almost the entire wage gap between cohorts was found to be due to worker heterogeneity. In particular, in line with the robustness analysis, the results suggest that favoritism of elder workers rather than positive productivity differences between elder and adult workers drives this heterogeneity and therefore plays a crucial role for the existence of pay differences across cohorts.

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', jobs' and industries' permanent heterogeneity. The method applied, allows to explain the conditional APG completely underlining the importance to account for various sources of heterogeneity (worker, job and industry) when it comes to differences in pay by age.

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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
young	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
Exper2	Exper squared
Tenure	Number of years worked for current employer
Tenure2	Tenure squared
	Fixed Effects
Individual_FEs	Worker FEs
Job_FEs	Job FEs
Industry_FEs	Industry FEs
Year dummies or Year FEs	One if the data was collected in either 2005, 2006, 2008, 2010, 2011 or 2014, zero otherwise; 2005 is used as base year

Table A.2: Descriptive Statistics on the Worker FEs, Full Sample

	(1)	(2)	(3)
Percentiles	Elderly	Young	Difference
10%	-0.347	-0.430	0.083
25%	-0.182	-0.282	0.1
50%	0.072	-0.097	0.169
75%	0.379	0.157	0.222
90%	0.643	0.410	0.233
Observations	8,240	16,553	

Table A3: Descriptive Statistics on the Job FEs, Full Sample

	(1)	(2)	(3)
Percentiles	Elderly	Young	Difference
10%	-0.023	-0.031	0.008
25%	-0.007	-0.007	0
50%	0.002	0.001	0.00034
75%	0.017	0.017	0
90%	0.023	0.023	0
Observations	8,240	16,553	

Table A4: Descriptive Statistics on the Industry FEs, Full Sample

	(1)	(2)	(3)
Percentiles	Elderly	Young	Difference
10%	-0.347	-0.430	0.083
25%	-0.182	-0.282	0.1
50%	0.072	-0.097	0.169
75%	0.379	0.157	0.222
90%	0.643	0.410	0.233
Observations	8,240	16,553	

Table A.5: Regression Log Net Hourly Wages with FEs

	(1)	(2)
	Standard FEs Regression	FEs Regression via Partitioned Procedure
Variables	Lhwage	Lhwage
young	0.007	0.007
	(0.009)	(0.004)
Tenure	0.001	0.001**
	(0.002)	(0.001)
Tenure2	-0.000	-0.000***
	(0.000)	(0.000)
Exper	-0.000	-0.000
	(0.003)	(0.001)
Exper2	0.000	0.000**
	(0.000)	(0.000)
Constant	2.114***	2.123***
	(0.080)	(0.011)
Year FEs	Yes	Yes
Worker, job and industry FEs	Yes	Yes
Observations	24,793	24,793

Robust standard errors in parentheses

$***p < 0.01, **p < 0.05, *p < 0.1$

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).