# The evolution of wage gaps between STEM and non-STEM graduates in a technological following economy

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## 1. Introduction

In a large body of literature the impact of technological change on labour demand is detected and measured through the pay gap between university and high-school graduates. According to the skill-biased technological change hypothesis, a widely held theory at first advanced to account for the widening of wage inequalities in the US labour market since the 1970s, new technologies are complementary to the skills provided by tertiary education and, as a consequence, give rise to a wage premium in favour of university graduates (Acemoglu 2002, Goldin and Katz 2008).

To this regard, in a comparative perspective, Italy turns out to be a country with a very low wage differential between high school and university graduates (OECD 2016). In a demand-supply framework this is at odds with the low tertiary education achievement rate. The explanation most frequently advanced to reconcile these facts is that labour demand in Italy has been less affected by new technologies complementing highly qualified labour (Visco 2010). Most available studies argue that the Italian economy is a laggard in the adoption of new technologies (Bugamelli et al. 2018, Schivardi and Torrini 2011).

Building on advances in the literature on the labour demand effects of new technologies, this study returns to this issue and provides a new attempt to uncover whether a significant technological change occurred in Italy in the last two decades and has had a visible impact on wage differentials. Recent studies on technological following countries have shown that the technological change is an endogenous process that may only occur when spurred by country-specific factors, primarily a large availability of skilled workers (O'Mahony et al. 2008, Blundell et al. 2018). This view motivates our study as in recent years Italy experienced a sudden and permanent increase in the flow of new graduates. This shock may have affected Italian firms and pushed them to finally adopt the ICTs.

Moreover, while studies are so far mostly limited to the wage differential between university and high school graduates, this cannot be regarded as a fully satisfactory approach as the average wage of all graduates, regardless of their field of study, gives only a rough measure of how the labour market rewards higher education, which possibly hides a large dispersion of tertiary graduates' wages.

We depart from this rather naive approach and focus on wage differences among university graduates across various fields of study. Two main arguments motivate this choice.

Firstly, as a larger amount of university graduates enter the labour market, the specialization conveyed by their degree becomes more important (Reimer et al. 2008, Altonji et al. 2016). The workers try to 'sell' and make the most of their set of skills, and the employers find it more convenient to select those best suited to match the skills required. Thus, specific fields of study gain importance in the labour market.

Secondly, as long as the set of knowledge and competences acquired in different fields of study are not perfect substitutes, both labour demand and supply must be analysed separately by fields of study. Technology represents one of the most relevant factors behind field-specific demand shifts.

To this purpose, following a large number of studies we assume that STEM graduates (graduates in Science, Technology, Engineering and Maths disciplines), who are provided with a sound quantitative background and a set of knowledge and competences well suited to match the ICT, are better equipped to develop and manage new technologies, and operate and interact in environments where technologies dictate the tasks and the languages (Goos et al. 2013, Webber 2014, Cho et al. 2018). From this point of view, it can be expected that technological change, at least in its initial, 'implementation phase', primarily increases the demand for graduates in these fields of study and, given the evolution of their supply, this is likely to trigger an increase in their wage premium (Beaudry et al. 2016).

This study investigates the wage differentials among fresh graduates who gained a degree in STEM subjects and graduates in other fields of study, namely Technical-Professionals (TP), Economics and Social Sciences (ESS), Humanities and Teaching (HT) in Italy over the period from 1998 to 2015. Through this analysis we aim at estimating how large wage gaps are between fields of study and how they have changed in order to assess whether their evolution is consistent with the occurrence of an economy-wide technological change. In our hypothesis, a positive wage differential in favour of the STEM group and its increase over time would be a signal that technological change occurred and had an impact on labour demand.

To accomplish our analysis we apply an Oaxaca decomposition and adopt a double selection procedure in order to address two sources of possible biases in the estimates, namely the selection into employment and the endogeneity of the choice of the field of study. This approach allows a pseudo-dynamic analysis to follow the evolution of the wage gaps and their components over the observed period of time.

Compared to previous studies, we update the analysis by extending the period observed well beyond the introduction of the major University reform that fuelled a striking increase in the flow of new graduates. This allows us to consider the possible medium-long run effects of that increase.

To the best of our knowledge, this is the first in-depth study focusing on the wage gaps by fields of study in Italy and covering almost two decades. Naticchioni et al. (2010) consider the educational wage premia from 1993 to 2004, using a sample of the working population aged between 15 and 64. As this introduces huge heterogeneity, we prefer elaborating on a sample composed only by cohorts of new graduates in their early career, who attended university and entered the labour market in the same years.

Ballarino and Bratti (2009) utilize the Istat-UGS on the new graduates over the period between 1995 and 2004. However, differently from our study, they only consider the employment outcomes with no regard to wages. Also other studies are concerned mostly with the employment outcomes rather than the wages of new graduates, or focus on specific geographic areas (Staffolani and Sterlacchini 2001; Checchi et al. 2004; Argentin 2010). A few others consider wage differentials by fields of study (Rossetti and Tanda, 2001; Di

Pietro and Cutillo, 2008; Buonanno and Pozzoli, 2009), however they do not offer any analysis of their evolution over time and seldom deal with the issues of the selection into employment and the endogeneity of the choice of the field of study.

The results show that raw wage gaps between STEM and the other fields of study after 3 or 4 years from graduation remain positive but on a downward trend. The wage gaps decline is even larger when adjusted wages (wages after correction for selection and endogeneity) are considered. On average, STEM graduates earn higher wages mainly because they are offered better jobs, however also the positive contribution of job characteristics shrinks over time. Finally, the unexplained part gives a substantial but declining contribution to the wage gaps too.

All in all, we did not find any evidence of such an increase in the STEM wage differential which would suggest that an impressive technological change was in progress. On the contrary, our results seem to confirm that technology adoption in Italy continues to be quite a weak process.

The rest of the paper is organised as follows. In section 2, we briefly discuss the related literature and specify our theoretical framework. Section 3 presents the data and descriptive statistics, while section 4 provides the model specification and the econometric strategy. Section 5 shows and discusses the main results and section 6 concludes.

## 2. Main hypotheses and background literature

To define our theoretical framework, we build on three different advancements in the literature on technological change and its effects on labour demand. First we consider that, contrary to the dominant view, maintaining that technological change is inherently skill-biased in as much as it implies a favourable impact on the demand for highly educated labour (Goldin and Katz, 2008; Katz and Margo, 2014), other studies show that the skills demand increasing effect of technological change is far from being constant over time and may also undergo a reversal. This is what occurred in the US since 2000 as shown by Beaudry et al. (2016), who argue that the introduction of new technologies is likely to give rise to a cycle in labour demand. At first, when technologies are implemented, there is an upsurge in cognitive tasks and the demand for skilled workers required to build the capital incorporating the new technologies. After that, when technologies reach their maturity, there is a weakening of the demand for skilled, highly educated labour. Similarly, Chun (2003) provides evidence that the labour demand impact of ICT changes over time. The initial increase in the demand for university graduates tends to be a temporary effect which comes to an end in the following phase, when the demand for graduates may only increase with the stock of ICT.

The distinction between the "implementation" and the subsequent "maturity" phases may well cause a divergence in the labour demand among countries. This is confirmed by O'Mahony et al. (2008) who analyse the UK and France besides the US.

The second advancement we build on concerns the sources of technological change. Blundell et al. (2018), in their analysis of the UK experience, depart from the view of a completely exogenous technological change, with a dominant technology adopted at the same time and equally affecting all advanced economies. They show that the UK, which was initially characterised by a scarcity of university graduates and lagging behind the US as regards to the share of highly educated labour force, has seen a huge increase in the share of graduates and surpassed the US in two decades. According to their reasoning, the increased supply of university graduates spurred the technological change in the UK which increased the demand for more educated workers. In their model, firms only adopt the ICT technologies when the share of highly educated workers in the labour force is high enough.

Third, we consider a number of studies showing that the wages paid to university graduates widely vary depending on the field of study (Grogger and Eide 1995, Reimer et al. 2008, Walker and Zhu 2011, Altonji et al. 2012, Altonji et al. 2016, Arcidiacono et al. 2012). Sloane and O'Leary (2005) find large heterogeneity of wage premia across groups of subjects and Chevalier (2011), after reviewing the available literature, concludes that there are wide differences in the returns on fields of study. Such differences tend to be even larger than the differences between academic institutions (Arcidiacono, 2004). Kirkeboen et al. (2016) demonstrate that large earnings gaps by fields of study persist even after controlling for differences in the quality of institutions and peer groups.

The natural reference group of graduates in an analysis aimed at inferring the occurrence of a technological change from the evolution of wage differentials is that of the graduates in STEM disciplines, as they are expected to be those ablest in managing and developing the ICT. Peri et al. (2015) and Winters (2013) find that a large share of STEM graduates has a significant effect on the productivity of other workers across US cities. Similar results are found also for Europe by Carneiro et al. (2018) who, based on Norwegian data, find that in areas with a larger increase in STEM workers there is a higher incentive to invest in new technologies. The close link between STEM and ICT is confirmed by Harrigan et al. (2018) on the basis of firm-level data for France. Also O'Mahony et al. (2008) distinguish between graduates in STEM and non-STEM occupations to detect the impact of technological change.

Moreover, STEM graduates turn out to be, in most cases, the best performing group in the labour market (Carnevale et al. 2011, Goos et al. 2013, Council of Canadian Academies 2015). They enjoy better employment prospects (Hamermesh and Donald 2008) and are more likely to get a full-time job within a year from graduation (Webber 2014, Cho et al. 2018). In their rich analysis of employment and wages of STEM workers in European countries, Goos et al. (2013) show that high-tech employment has grown at twice the rate of overall employment, and high-tech workers are paid wages which are well above the average wage. The authors interpret this evidence as a confirmation of an intense increase in the demand for high-tech skills.

As for Italy, Naticchioni et al. (2010) show that, unlike other European countries, the return to tertiary education decreased in Italy, and conclude that the skill-biased technical change hypothesis does not fit the data. However, they observe only the period just before the impact of the major University reform that increased the flow of graduates.

In a study based on data from the Istat-UGS, Ballarino and Bratti (2009) scrutinize the early employment prospects of Italian fresh graduates in the period 1995-2004. They find that graduates from quantitative fields face better prospects. However, since there is no further increase in their relative performance over time, they reject the hypothesis of a relevant skill-biased technical change. Similar conclusions are reached by Buonanno and Pozzoli (2009). Also Argentin (2010) reports significant differences in labour market outcomes between fields of study.

Overall, the advancements in the literature briefly summarised here imply that the technological change cannot be seen as a sort of windfall involving all countries at the same time and with identical effects. Instead, we take the idea that technological change is more likely to occur if the required country-specific conditions are satisfied, implying that different national trajectories of technological change may arise. In particular, no technological change may happen if the economy is in short supply of skilled workers. Italy is a technological follower characterised by a low though increasing share of graduates (Schivardi and Torrini, 2011). Then, arguably the relative scarcity of university graduates prevented firms from adopting new technologies up to the early 2000s. Since then, the sudden and permanent increase in the flow of new universities graduates might have created a more favourable environment for technological change.

That makes plausible that, similarly to what happened in the UK, Italian firms have reacted to this supply shock by implementing new technologies. In that case, it should be expected an upward shift in the demand for highly educated. If this shift is large enough, it should cause an enlargement of wage differentials. To detect this demand-increasing effect we consider the wage differentials between the STEM and the other groups of graduates.

An increase in these wage differentials and in its unexplained component estimated by the Oaxaca decomposition would be consistent with the hypothesis that a technological change has occurred in the Italian economy. However, in case of a decline in the STEM-non STEM wage differentials, the interpretation should be more cautious. Indeed, on the one hand, this may point out that no major technological change occurred, and that the Italian economy continues to be a laggard in technology. But, on the other hand, it could also be argued that the adoption of new technologies in the Italian entrepreneurial environment is likely to rely less on cognitive and formal skills and more on social and soft skills, which are poorly accounted for by educational degrees. In such a case the effects on the demand for skills would be somewhat different from what expected on the basis of the experiences of other countries.

As our results clearly show a decline in the STEM wage differential, we will discuss this in more detail when commenting on the results.

## 3. Data and descriptive statistics

We analyse data from different waves of the University Graduates Survey (UGS), conducted by the Italian National Statistical Institute (Istat). The survey covers a representative sample of tertiary graduates in Italy interviewed three/four years after graduation and provides detailed information on educational and labour market careers of university graduates, as well as their parental background characteristics. Six waves are available, from 1998 to 2015.

Due to the peculiarities of their school to work transitions, graduates from Medicine and Military Academies have been removed from the samples. Moreover, we restrict our analysis to the dependent workers as we are interested in considering also how graduates sort into jobs with different types of contracts according to their field of study.

Our analysis compares the early wages of four different groups of graduates: STEM (graduates from Sciences, Technology, Engineering and Mathematics groups); Technical Professionals (graduates from Chemical-pharmaceutical, Geo-biological, Architecture and Agrarian groups); Economics and Social Sciences (graduates in Economics, Statistics, Political Science, Law and Psychology); Humanities and Teaching (graduates from Literary, Linguistic and Teaching groups, including Physical Education). Even though it prevents us from considering the whole graduates' career evolution, focusing on the early wages of new entrants into the labour market enables us to better understand the latest trends in labour demand (Beaudry et al. 2016).

Descriptive statistics of the main variables are shown in table A1 in the Appendix[1]. It is worth noticing that three-quarters of the STEM graduates are males (against 10% of graduates in HT). Overall, STEM graduates got higher grades at the end of high-school (88.9/100, against little more than 80 for other graduates), but they took longer to get their university degree and got lower university grades. After gaining their degree, they appear to be concentrating in Manufacturing and Information & Communication sectors, whereas graduates from ESS and HT courses appear to be more represented, respectively, in Finance and in Education & Health sectors. Also note that STEM graduates are less interested in fixed-term and part-time contracts or employment in the public sector. Besides, they are far less affected by overeducation compared to all the other groups of graduates.

As a measure of the workers' compensation we consider the monthly wage. We prefer it, not only because this is the information collected by the survey, but also because it represents a more comprehensive measure in order to assess the global return to education. Indeed, monthly wages depend on the whole set of job's characteristics, including the hourly wage and the working hours, and can be considered as a better measure of the labour market prospects of newly graduate students. Nevertheless, hourly wages by fields of study, as well as working hours and employment rates 3 or 4 years after the degree, are reported on Table A2 in the Appendix[2]. Table A2 shows that STEM hourly wages are not much higher than non-STEM ones. As a matter of fact, during certain years, they are very close to HT wages. The main advantages of STEM graduates over non-STEM ones consist of a higher number of hours worked per month and a higher employment rate[3]. All

[1] Note that some covariates (such as firm size and public employment) are not available in all the waves of the UGS dataset. However, as we consider these variables important for the purpose of our analysis, we include them in the estimations when possible.

[2] Table A2 also reports the STEM overall earning gap. The calculation of this indicator is analogous to that of the gender overall earning gap, proposed by Eurostat (2017).

[3] Note that STEM (and TP) employment rates dropped sharply in the 2007 survey. This seems to be due, more than to labour market conditions, to the introduction of the 3+2 reform that pushed STEM graduates, more than other ones, to keep on studying in order to get a second level degree (see Table A1).

this entails a large "overall earning gap" between STEM and non-STEM, in particular with reference to the HT group.

In any case, analysing wage gaps by fields of study is a very important issue, especially in a country like Italy where the wage gap between upper-secondary and tertiary graduates is traditionally low. Figure A1 (in Appendix) shows that in some years the magnitude of the differential in monthly wages between STEM and non-STEM graduates is analogous to the differential between monthly wages of upper-secondary and tertiary graduates as a whole. That is, the choice of field of study may influence wage inequalities to almost the same extent as the choice of enrolling or not into university. Nevertheless, it is worth noticing that both wage differentials have been declining for years until 2011 and that a slight recovery was manifested only in 2015.

The above illustrated wage evolution has taken place in a context of instability of enrolment rates in Italy. The percentage of high school graduates who enrolled in university increased immediately after the so called "3+2 reform", but it has been declining since the 2003-04 academic year (Figure A2 in Appendix). Despite this, the total number of tertiary graduates has remained substantially stable since 2005 after the sharp increase of the early noughties (Figure A3 in Appendix).

Even though there has been a notable increase in the total number of new graduates entering the labour market, the relative supply of STEM graduates (defined as the ratio between STEM and non-STEM graduates) is far from increasing. Actually, it fell by 1.9 percentage points between 2003 and 2011 (Figure A3). In a demand-supply framework, this evolution of the supply of STEM is at odds with the decrease in the STEM/non-STEM wage gap and suggests that the relative demand for STEM must have fallen in the same period.

## 4. Econometric strategy: an endogenous switching model with sample selection

To accomplish our analysis we adopt the Oaxaca decomposition method. This enables us to decompose the earnings differentials between STEM and the other non-STEM groups of graduates[4] into an explained component (the "endowment" effect, depending on the characteristics of the subgroups) and an unexplained component (the "returns" effect).

To perform the Oaxaca decomposition we need to estimate two wage equations for Stem and non-STEM graduates:

$$lnY_{ij} = X'_{ij}\beta_j + e_{ij}, \qquad [1]$$

[4] For the sake of simplicity, we present our econometric model as if we were to decompose the earning differential between STEM and no-STEM.

where $j$=$s$,$ns$ refers to STEM ($s$) and non-STEM ($ns$) groups and $i$ to individuals. X is a vector of household, individual and job characteristics[5] that may influence wages and $e_{ij}$ is the error term.

In this model two hypothetical sources of misspecification can arise.

First of all, as the wage is observed only if the individual actually works, we have a classical Heckman's (1979) sample selection bias due to the selection in employment. Thus, we have the following latent variable for the selection in employment:

$$E_i^* = K_{i\,j}'\,\theta + \nu_{ij}$$

In this case we estimate the following probit model:

$$E_i = \begin{cases} 1\ if\ \ E_{i\,j}^* > 0 \\ 0\ otherwise \end{cases}$$

where the set of explanatory variables $K$ comprehends individual characteristics (among which, high school and tertiary education final grades, a dummy for delayed graduation and a set of dummies for fields of study) and household characteristics (such as social class and parents' education level) of the individual $i$. By regressing this model we calculate the selection term[6], $\delta_i$, to be added to the wage equations in order to take into account the selection in employment.

The wage equations [1] to be estimated become:

$$lnY_{ij} = X_{ij}'\beta_j + \hat{\delta}_i\kappa_j + \omega_{ij}, \qquad [2]$$

The second source of misspecification arises from the fact that we do not observe the indirect utility ($S_i^*$) of enrolling into a STEM course for individual i:

$$S_i^* = Z_i'\,\alpha + \varepsilon_i$$

Instead, we only observe if the individual enrolled in a STEM or a non-STEM course. As individuals self-select into different fields of study, we cannot exclude the presence of unobservable factors affecting both the choice of field of study and the rewards accruing to individuals in the specializations they choose. Thus, the major's choice is endogenous. As a first move to deal with this issue, we include in our model a number of covariates referring to the school curriculum and to the family background of the graduate. Indeed, these factors represent the most important determinants of the choice of the field of study in the Italian context (Ballarino and Bratti 2009, Checchi and Flabbi 2013). Moreover, as a second move, we estimate an endogenous switching model which takes into account the sample selection into employment[7].

[5] The list of the main variables we use in our analysis is illustrated in Table A1. As some research put in evidence that wage inequality within Italian college graduates can partly be ascribed to the heterogeneity of educational institutions' quality (Ordine and Rose, 2011), we also control our estimations by attended athenaeum.

[6] The selection term is calculated as: $\delta_i = \frac{\phi(K_i'\,\theta)}{\Phi(K_i'\,\theta)}$, where $\phi(.)$ and $\Phi(.)$ denote, respectively, the density and the cumulative normal distribution functions of the standard normal.

[7] Wooldridge (2010), pp. 809-813.

In the first stage, we estimate the following Probit model:

$$S_i \;= Z_i' \alpha + \hat{\delta}_i \kappa + \varepsilon_i \begin{cases} = 1 \; if \;\; S_i^* \geq 0 \\ = 0 \; if \;\; S_i^* < 0 \end{cases}$$

and we calculate the selection term[8] ($\lambda_{ij}$) to be added as a new regressor in the wage equations.

Unadjusted OLS estimations of wage equations [2] do not take into account the co-variation between the explanatory variables and the selectivity variable $\lambda_{ij}$ and could be biased. $\lambda_{ij}$ accounts for the influence of the decision process (STEM/no STEM) on the dependent variable (wages).

Then, the wage equations will be estimated by taking into account the selection in employment (through $\hat{\delta}_i$) and the endogeneity of the major's choice (through $\hat{\lambda}_{ij}$).

The Oaxaca decomposition between raw mean wages is as follows:

$$ln\bar{Y}_s - ln\bar{Y}_{ns} = (X_s' - X_{ns}')\hat{\beta}_s + X_{ns}'\left(\hat{\beta}_s - \hat{\beta}_{ns}\right) + \left[\left(\bar{\lambda}_s\hat{\gamma}_s - \bar{\lambda}_{ns}\hat{\gamma}_{ns}\right) + \left(\bar{\delta}_s\hat{\kappa}_s - \bar{\delta}_{ns}\hat{\kappa}_{ns}\right)\right] \qquad [3]$$

where the first term on the right represents the "endowment effect", the second term the "coefficient effect" and the third term accounts for the selectivity and endogeneity effects.

To the purpose of our analysis, variables X in equation [3] are distinguished between individual (Q) and job characteristics (Z), so that the Oaxaca decomposition between the adjusted mean wages can be written as:

$$ln\bar{Y}_s^{adj} - ln\bar{Y}_{ns}^{adj} = \left\{(Q_s' - Q_{ns}')\hat{\beta}_{Q_s}^{adj} + (Z_s' - Z_{ns}')\hat{\beta}_{Z_s}^{adj}\right\} + \left\{X_{ns}'\left(\hat{\beta}_s^{adj} - \hat{\beta}_{ns}^{adj}\right)\right\} \qquad [4]$$

In both stages of our empirical model we need at least one suitable instrument. In particular, referring to the selection into employment, we need an instrument which is correlated with the probability of being in employment but not with wages. For the sake of homogeneity among the waves of Istat data we use in the analysis, we decided to use a dummy for married individuals. As a matter of fact, the possibility of creating a new family is strictly tied to being employed. On the contrary, it seems reasonable to assume that married and non-married wages are rather compressed for young graduates in our sample, taking into account that they are at the beginning of their experience in the labour market. However, in order to control for the validity[9] of this instrument, we have performed the test proposed by Dolton and Vignoles (2002). The results, reported in Table A5 at the end of the Appendix, support our assumption.

As to the issue of the endogeneity of majors' choice, we need a variable correlated with the probability of enrolling into a STEM course at university, but not with wages. In this case, we use a dummy for individuals

[8] In this case the selection term is defined as: $\lambda_i = \frac{\phi(.)}{\Phi(.)} \; if S_i = 1;\;\; \lambda_i = -\frac{\phi(.)}{1-\Phi(.)} \; if S_i = 0$, where $\phi(.)$ and $\Phi(.)$ are the density and the cumulative normal distribution functions of the standard normal.

[9] A valid instrument must be uncorrelated with the error term of the outcome equation, and thus it should not affect wages conditional on the included explanatory variables. When the residuals from the wage equations were regressed on the instruments, we obtained very low R2 values (see Table A5). This indicates that the instruments do not explain any significant variation in the residual variability and hence are valid.

who attended a scientific high school (*Liceo Scientifico*) before university. Indeed, it is widely accepted in the economic literature that, even in the absence of formal entry requirements, the type of pre-university knowledge significantly affects subject choice at university (Altonji 1993; Van de Werfhorst et al. 2003). As for Italy, it has been recently shown that strengthening high school science curricula affects the choice of enrolling in and completing a STEM degree at university (De Philippis 2017). On the other hand, we do not have a strong *a priori* about the importance of high school curriculum for graduates' earnings, once we control for the tertiary degree subject (Bratti and Macini 2003).

Even in this case the test of Dolton and Vignoles (2002) supports this choice (Table A5).

Note that many papers dealing with wage differentials by field of study do not address the problem of the selection in employment. Altonji et al. (2012) argue that this problem is negligible for men and that the results on the male sample would represent the unbiased estimates. By contrast, Hamermesh and Donald (2008) address it by instrumenting the labour force participation by the presence of young children.

As to the endogeneity of the subject choice, most papers address it simply by including more controls in the estimated equations (Chevalier 2011). In a study next to our work, Sloane and O'Leary (2005) include in the estimations a measure of students' ability.

Then, unlike a large part of the existing literature, we try to take explicitly into account both the hypothetical sources of misspecification in order to achieve more reliable results.

## 5. Estimation results

The raw wages of every group show a clear tendency to increase during the period under analysis (Figure 1), while the unadjusted wage differences between STEM graduates and the other groups tend to decrease. This tendency is quite sharp for the TP group only in the first part of the observed period (Figure 2.a), while it continues till 2011 for ESS and TH groups (Figures 2.b and 2.c). On the contrary, all three differentials increase at the end of the period, between 2011 and 2015.

FIGURE 1 ABOUT HERE

FIGURE 2.a ABOUT HERE

FIGURE 2.b ABOUT HERE

FIGURE 2.c ABOUT HERE

The raw differentials may be affected by unobserved individual characteristics if people with different abilities (motivations, ambitions, effort propensity) do not distribute randomly across fields of study and between employment and out of the labour force. Then, we have to consider the adjusted differences. Figures 2.a, 2.b and 2.c make clear that the selection bias is substantial as the raw and adjusted differences do not overlap. The distance between raw and adjusted differences is lower during the sub-period 2001-2007 while it widens afterwards, meaning that the unobserved heterogeneity becomes more influential in 2011 and 2015.

More precisely, as the adjusted differences curves lie below the raw differences curves, we may argue that abler individuals sort themselves more frequently into STEM fields of study and that the ablest of them are selected into employment.

A possible explanation of the enlargement of the differential between raw and adjusted wage gaps in 2011 relies on the observation that individuals interviewed in 2011 graduated in 2007 and most of them, presumably, enrolled into university after the 2001 "3+2 reform"[10].

The 2001 reform has determined deep changes in the supply of university courses. In particular, the traditional 4–5-year programmes have been replaced by the implementation of a three-level structure, constituted by a first-level degree (Laurea Triennale, 3 years), a second-level degree (Laurea Magistrale, 2 years), followed by doctoral studies (Dottorato di Ricerca, 3 years)[11]. Then, for the largest part of the courses the required duration was shortened. University curricula deeply changed and the variety of the courses increased suddenly, as a large number of new courses were introduced for the first time. The denominations of the courses changed as well (Argentin and Triventi 2011).

This major system reform contributed to the substantial increase in the number of graduates until 2005, and to its subsequent stabilization since then at much higher values than at the beginning of the noughties (Figure A3). It has been shown that as a greater number of people entered university and achieved a degree, the increase in the quantity came together with substantial changes in the quality of the graduates. In particular, Di Pietro and Cutillo (2008) show that the "3+2 reform" attracted into Italian universities a greater number of students to the detriment of the average quality of enrolled students[12].

Our evidence on the comparison between adjusted and unadjusted wage gaps suggests that this deep reshape and enlargement of the university offer, and the related increase in enrolments and graduations, has worsened the average quality of enrolled/graduated students, mainly affecting non-STEM courses[13]. In other words, after the reform non-STEM courses have disproportionately attracted less able students. As a consequence, the relative average ability of STEM graduates has ameliorated with respect to non-STEM graduates, and this may explain the larger distance between unadjusted and adjusted wage gaps since 2011[14].

[10] On the contrary, individuals interviewed in the 2007 survey graduated in 2004, and only a few of them enrolled into the new courses introduced by the "3+2" reform.

[11] Based on the information gathered in the survey Questionnaires of different years, we are able to distinguish among different type of graduates (old degree, first-level degree and second-level degree) and to include a specific series of dummies in our empirical models.

[12] The opposite situation has occurred as a consequence of the Great Recession that hit Italy in 2008 (Ghignoni 2016).

[13] As a matter of fact, the ratio between the number of STEM and no-STEM graduates keep on decreasing from 2004, with a recovery only in the last years (Figure A3).

[14] This result is in contrast with that obtained by Webber (2014) on the lifetime earnings premia of three birth cohorts of US graduates. In that case, the unadjusted wage gap between STEM and Arts/Humanities graduates becomes thinner over time. However, after taking into account the selection into different majors, the author concludes that much of the change can be explained by the recent worsening of the relative ability of STEM students.

In the next step of our analysis we apply the Oaxaca decomposition to the three differentials between the mean adjusted wages of the STEM and the other groups. In each of the three decompositions the explained part, that is the part ascribable to individual characteristics and job features, is largely prevailing as it accounts for 70% up to 85% of the wage gap.

However, individual characteristics play only a limited role while the job features explain by themselves the largest part of the gaps (Tables A3.a; A3.b and A3.c) meaning that STEM graduates result to be only slightly better endowed, while they face substantially better employment opportunities than graduates from other fields of study[15].

Conversely, the size of the unexplained part**,** which depends on the value of the set of knowledge and competences provided by the field of study as assessed by the labour market, is more limited, though still relevant. It accounts for 15% and 18% for the wage gap between STEM and, respectively, TP and ESS groups, while it reaches 28% for the HT group (Table A4). Within the unexplained part, in some years the return to the characteristics of the job is negative (Tables A3.a, A3.b and A3.c), pointing out that STEM graduates enter better jobs but get lower returns on them. In the differential between STEM and TP groups also the returns to individual characteristics exert a negative, though very limited, effect in the mean of the period. On the contrary, in the other two comparisons they show a positive sign.

As reported also by Cho et al. (2018), our results show that most of the wage differentials (after controlling for selection processes) depend on the fact that STEM graduates are able to get better jobs, namely those jobs that pay higher wages on average. Overall, they have better chances of working in larger firms and with permanent contracts. Conversely, they are less overeducated. The single most influential job characteristic is working time. In each comparison STEM graduates are more likely to get a full-time job. The same finding is shown by Webber (2014). Several authors find similar results and argue that the kind of jobs that graduates are able to get may be regarded as a consequence of their specific field of study (Chevalier 2011, Sloane and O'Leary 2005, Longhi et al. 2013). This reflects the fact that jobs for skilled people from different fields of study are unevenly distributed across firms, sectors and occupations, and that the job offers they receive differ not only according to the current wage level *per sé*, but also according to other aspects of the employment relationship, like working time, stability or overeducation.

From the evolution over time of the decomposition results it arises that the effect of the individual characteristics, besides being almost negligible, is also decreasing over time. In particular, graduates in the STEM and TP groups may be considered almost identical as far as their personal profile is concerned (Figure 3.a). The single most influential characteristic is gender[16] (female) but it loses significance after 2004 (see Table A3.a). Conversely, the characteristics of the jobs, as already noted, represent the most important set of factors contributing to the wage gap. The unexplained component is on average less important than the explained one and quite unstable over time. Since 2001 this component shows a negative trend: while in 2001

[15] The variables that contribute significantly to the explanation of the wage gaps are concentrated among those related to job characteristics, with the remarkable exception of the variable "gender".

[16] Note that the quota of female STEM graduates is, approximately, 1 out of 4 (Table A1) and that it has been growing very slowly during the period under observation.

it explains 10 log points of the wage gap, at the end of the period it turns to a negative contribution to the wage gap.

FIGURE 3.a ABOUT HERE

FIGURE 3.b ABOUT HERE

FIGURE 3.c ABOUT HERE

A similar pattern is shown by the decomposition of the gap between STEM and the ESS group (Figure 3.b). The individual characteristics play a minor role. The only individual characteristic which exerts a relevant role is gender and its effect decreases over time. This depends, on the one hand, on the fact that the presence of females in the two groups tends to become less uneven over time and, on the other hand, that the wage gap by gender grows smaller (Table A3.b). The contribution of the job characteristics represents the largest component of the wage gap and decreases until 2011. Even in this case the unexplained part exhibits wide changes and falls after 2004.

Finally, the results of the decomposition of the gap between STEM and HT graduates show that individual characteristics give a considerable contribution at the beginning of the period, but their weight diminishes from then on (Figure 3.c). As in previous cases, the effect of gender, which was the most important effect associated with individual characteristics, falls over time. Even the job characteristics lose a substantial part of their effect. As for the unexplained part, it shrinks up to 2011.

To sum it up, the results of the three decompositions show very similar dynamics over time. The individual characteristics have little influence and tend to become even less influential, pointing out increasing similarities between graduates belonging to different fields of study. On the contrary, the part of the wage gaps explained by job characteristics is large. This clearly shows that graduates in different fields of study are offered different jobs. In particular, STEM graduates face a lower risk of working part-time and under a temporary contract. At the same time, they are more concentrated in sectors that pay higher wages, and in larger firms. Notably, they seem less affected by overeducation problems (Tables A3.a, A3.b and A3.c). However, even this component falls over time until 2011, meaning that the jobs offered to the different groups become increasingly less different over time.

The unexplained part shows a clear negative trend which is reverted (apart from the TP group) only in 2015. The unexplained part in our analysis measures the effects of all unobserved factors and, in particular, it captures the effects deriving from the set of knowledge and competences provided by each field of study.

According to our main hypothesis, the advent of a technological change and of its initial, implementation phase, should imply an increasing wage gap in favour of the STEM group. Our results do not fit at all this prediction. First of all, the wage differentials and, most importantly, the adjusted wage differentials, are declining over time until 2011. The largest part of the gaps is explained by differences in job characteristics, but even this advantage declines over time. Moreover, most of the decrease in the pay gaps derives from the decrease in the unexplained component and, to a lesser extent, also from the lowering of the effect of the job characteristics. Both these facts signal a declining relative reward paid by the firms to the set of knowledge and competences acquired through graduation in the STEM fields of study.

However, as already noted in section 1, the interpretation of these results requires some caution. On the one hand, it may be concluded that no substantial technological change has occurred in that period. On the other hand, one may guess that a technological change has occurred but its effects on the labour demand for skills cannot be captured by considering educational degrees as it involves a broader range of skills.

The first reading is our preferred explanation as it is consistent with large evidence on the Italian economy. The relative earnings of graduates in Italy are low despite the low share of people holding a tertiary degree in comparison with other advanced economies. These facts, which make Italy an outlier in a comparative perspective, may be reconciled assuming that technological change so far had only a limited impact on labour demand. This explanation fits other features of the Italian economy, especially the large share of small businesses and the low investments in R&D, pointing out that technological innovation concerns only limited sections of the economic system (Cipollone et al. 2012). Schivardi and Torrini (2011) show that some of the peculiar characteristics of Italian firms, above all the technological content of their activity, explain their scant propensity towards the adoption of new technologies. Also the low level of the employers' education tends to restrain innovation, particularly for small businesses (Croce et al. 2015). On the basis of these results it is plausible to argue that major obstacles to the technological change derive in Italy also from structural features of labour demand rather than only from the shortage of university graduates supply *per se*.

Figure 4 gives a clear picture of the weakness of the adoption of new technologies by Italian firms. The share of ICT investments on total investments is below that of the US and the UK but similar to that of France and Germany till 1995. From that year on, ICT investments make a jump also in the latter two countries while they stagnated in Italy and even declined since 2000.

FIGURE 4 ABOUT HERE

As already noted, many researchers argue that the skill-biased technical change hypothesis does not fit Italian data (Buonanno and Pozzoli 2009, Ballarino and Bratti 2009, Naticchioni et al. 2010). Others find that there is not any clear effect of new technologies on labour demand (Cipollone et al. 2012, Schivardi and Torrini 2011, Bugamelli et al. 2018).

Moreover, our results contrast with the idea that the evolution of the wage gaps was mainly driven by the flexibilization of the labour market (Law 196/1997, known as "Pacchetto Treu" and Law 30/2003, Biagi Reform). According to this hypothesis, STEM graduates would have been more involved in the diffusion of temporary work and other forms of sub-optimal employment than non-STEM graduates. Nevertheless, the Oaxaca decomposition does not provide evidence that the evolution of flexibility hit harder STEM graduates. Depending on the particular group of comparison, the job characteristics that mostly explain the relative deterioration of the wage gap are firm size and sector. Temporary contracts are relevant only in the comparison with the ESS group, but the magnitude of the effect is always very limited.

Other macroeconomic and institutional shocks occurred in the observed period may have affected asymmetrically the wage of different groups of graduates, so as to confound the effect of technological change on wage gaps. However, macroeconomic and institutional shocks do not affect directly the groups of graduates in different fields of study *per se*, but as an indirect effect of their position in the labour market. Then, by controlling for sector, occupation, type of contract, firm size, geographical macroareas and a large set of other wage determining factors, most of the influence of the shocks is taken into account. Then, in this view it is clear that there was no technological change influential enough to widen the wage gaps in favour of the STEM graduates.

However, according to the second reading, it can be argued that in the Italian entrepreneurial environment the technological change is likely to affect the labour demand differently from what is experienced in other economies. In particular, new technologies may complement more social and soft skills than cognitive and formal skills. This implies that analyses based on educational degrees cannot take a full picture of the labour demand effects of technology.

Deming (2017) shows that since 2000 the return on cognitive skills and the share of STEM jobs have declined in the US. At the same time, employment has increased in occupations implying social interactions, which are also characterised by tacit knowledge. Quite surprisingly, wages in jobs with social skills have increased more than wages in jobs with cognitive skills. Overall, social skills have become more important over time as a consequence of technological change. As shown by Levy et al. (1999) in their study on the automobile service and car sales activities, the effect of the technological change is often much less clear-cut than what it is supposed to be according to the skill-biased technical change hypothesis, as its impact varies widely across occupations. Similarly, Baccini and Cioni (2010), who focus on an Italian industrial district, find that some of artisanal occupations are not displaced by the advent of computers.

These findings suggest that technologies may increase the demand not only for workers provided with strictly quantitative skills required to develop and manage new technologies, but also for those who possess a broader mix of skills and, at the same time, may leave others unaffected (World Economic Forum 2016). The increasing importance of tertiary activities and occupations in advanced societies pushes firms to prefer generalist graduates, with good communicative, relational and creative skills who are able to adapt to different jobs and tasks (Ballarino and Bratti 2009). That being so, also non-STEM graduates, who are characterized by less narrow technical knowledge and competences, might be favoured by this evolution. Rather than requiring a larger number of engineers and computer scientists able to develop and manage complex technological systems, the diffusion of the ICT technologies may prompt the demand for workers able to use them in various contexts in combination with social and creative skills. This hypothesis fits some features of the Italian production system, which is characterised by a disproportionate incidence of small and family businesses, and is heavily dependent on tacit knowledge (Antonelli et al., 2014, Federici et al. 2008, Belussi and Pilotti 2000, Bugamelli et al. 2012, Hall et al. 2012).

An empirical test of this hypothesis goes behind the limits of our study as it would require detailed information on the full range of skills demanded by the firms, cognitive as well as social and soft skills, behind the formal educational degrees. Unfortunately, this information is not easily available for samples representative of the whole or large portions of the economy. Then, in the case of a decline of the wage differentials between STEM and the other groups we can only speculate on the basis of the available evidence in order to tentatively choose the most suitable interpretation of our results.

## 6. Conclusions

This study aims at uncovering whether a technological change occurred in Italy in the last two decades. Italy is unanimously considered a laggard in the adoption of new technologies, however, at the beginning of the 2000s it underwent a major upsurge in the flow of new university graduates. According to the experience of other technological following economies, this shock in the supply of highly educated workers might have driven the advent of a technological change. This is what motivates this study, that covers a period well beyond the early 2000s in order to ascertain whether the rise in the supply of tertiary graduates was followed by an increase in the demand for skills.

To this purpose we depart from the more usual analysis of the pay gap between university and high school graduates and consider instead the wage differentials among university graduates from different fields of study under the assumption that the set of skills characterising different fields of study do not match the new technologies in the same way.

We deal with both the issues of the endogeneity of the choice of the field of study and the selection into employment. Next, we apply an Oaxaca decomposition to the differences between mean adjusted wages of STEM and other three groups of graduates.

Our results show that in certain years the magnitude of the positive wage differential between STEM and non-STEM graduates is equivalent to the difference between the wages of upper-secondary and tertiary graduates. That is, the choice of the field of study influences wage inequalities almost to the same extent as the choice of enrolling or not into university.

All in all, we do not find any evidence of an increase in the STEM wage differential. On the contrary, the unadjusted wage differentials and, most importantly, the adjusted wage differentials, are declining over time, until 2011. The decomposition reveals that the contribution of the individual characteristics is low and decreasing. The largest part of the gaps is explained by the differences in job characteristics, pointing out that STEM graduates are more likely to get better jobs, but even this advantage declines over time. Finally, also the contribution of the unexplained part narrows until 2011.

Thus, the evolution of labour demand in the Italian economy does not reveal that any substantial technological change has occurred in the last two decades in the Italian economy. However, caution is required in interpreting these findings. Indeed, it could be argued that the adoption of new technologies in the Italian entrepreneurial environment is more likely than in other economies to rely on social and soft skills, which are poorly accounted for by educational degrees. In such a case future research should investigate more in depth this issue by considering information covering a more comprehensive notion of skills.

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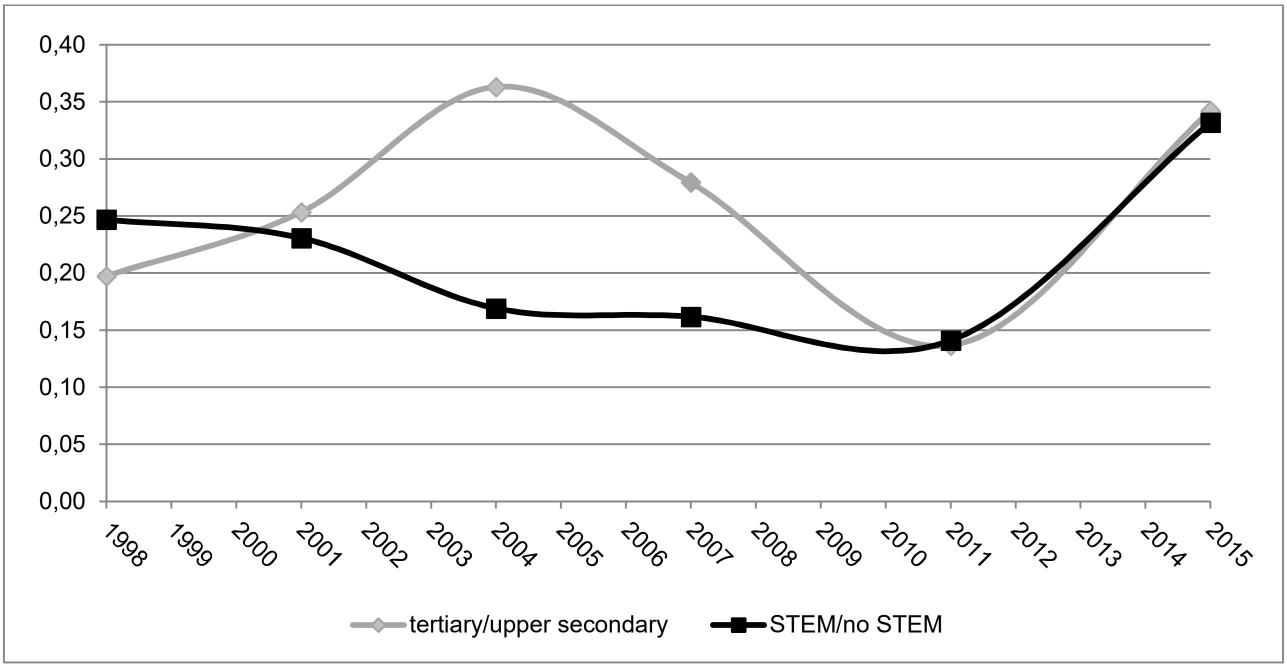
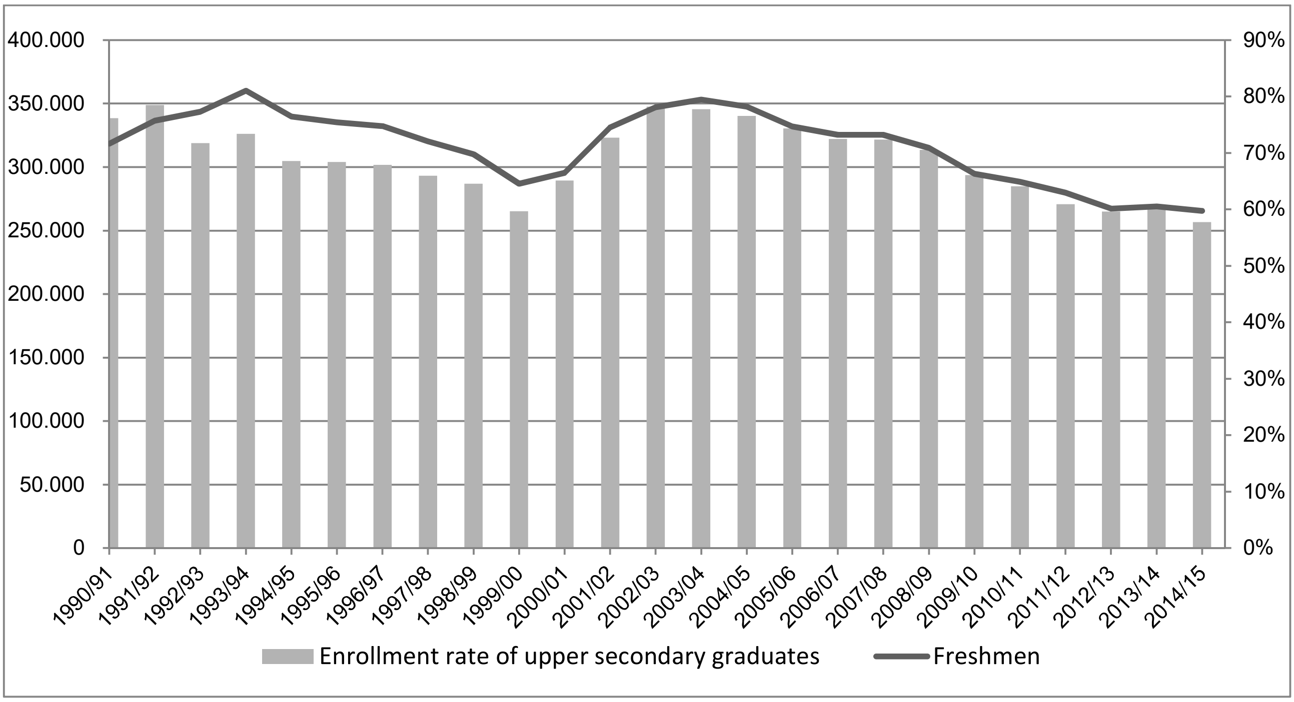
**Figure 1 – Raw monthly wage differentials (log) between tertiary–upper secondary graduates and STEM–no STEM tertiary graduates, Italy, 1998-2015**



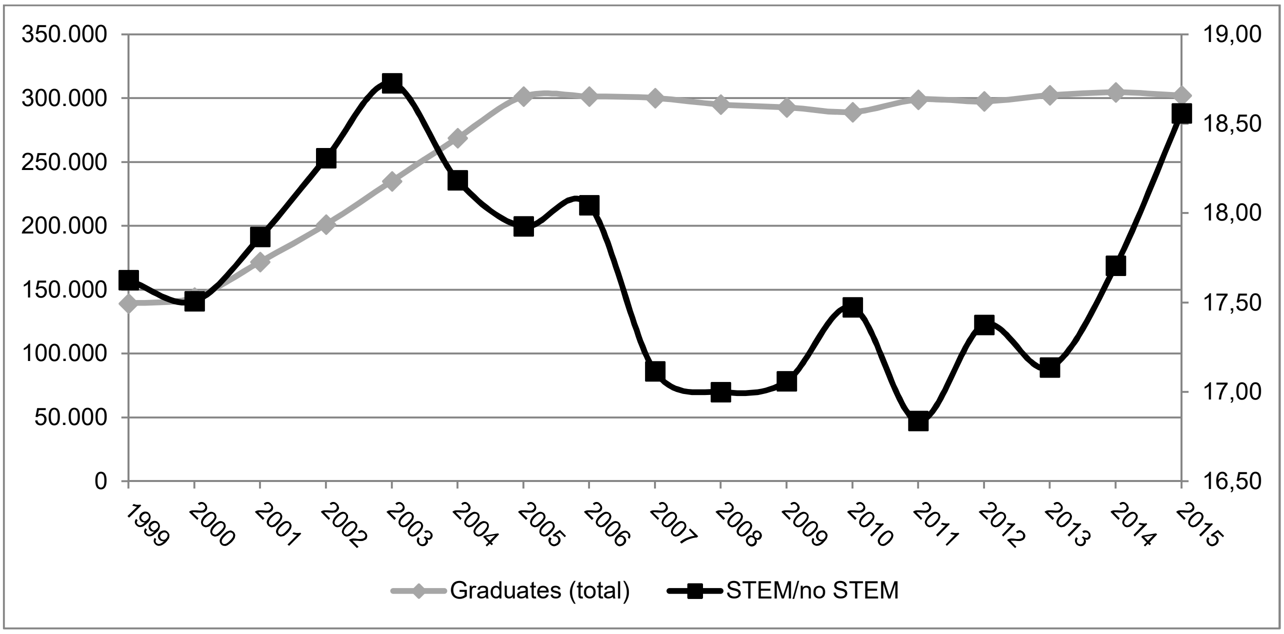

Source: Elaboration on UGS data, ISTAT, various years.

**Figure 2 – Freshmen per academic year and enrolment rates, Italy 1990-2015**



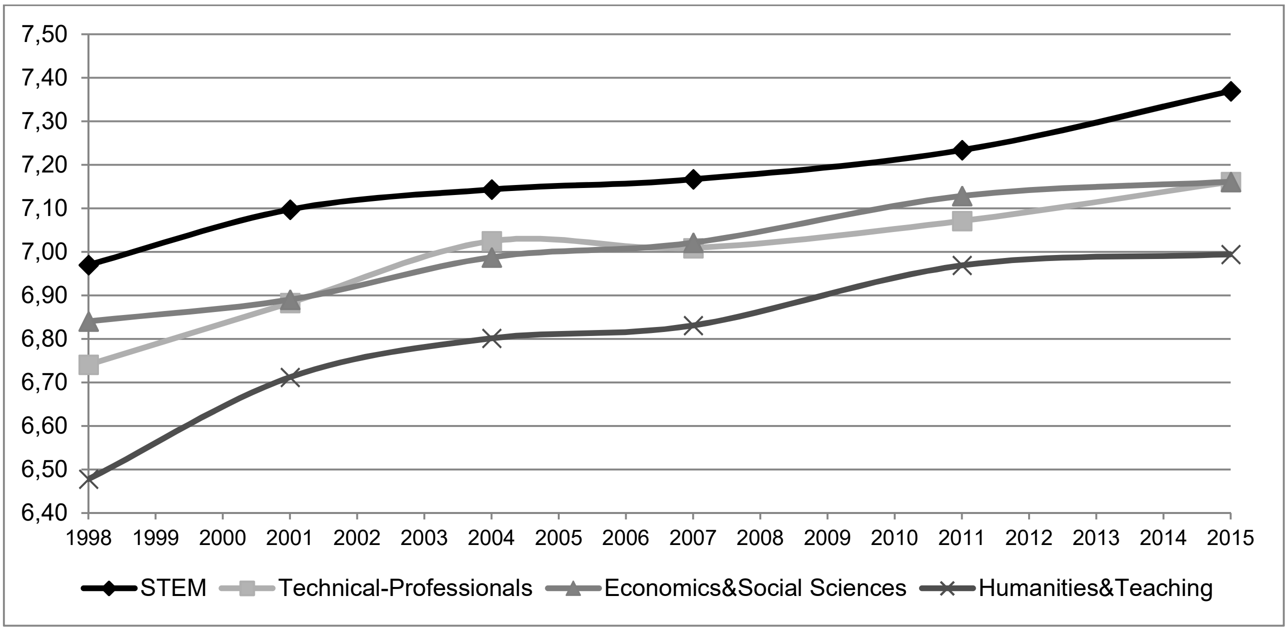

Source: elaborations on MIUR/ISTAT data

**Figure 3 – Total number of tertiary graduates and ratio STEM/no STEM, Italy, 1999-2015**



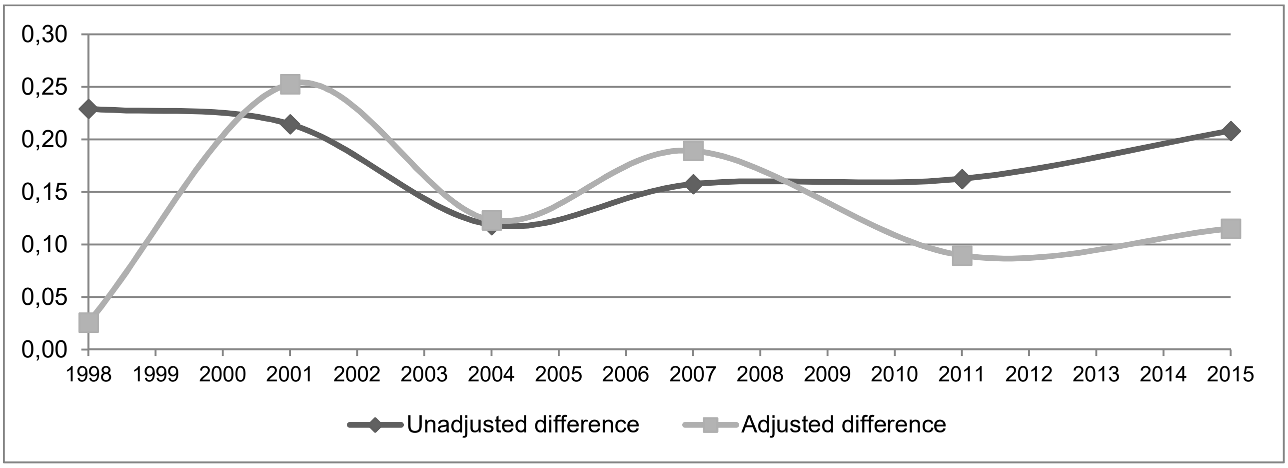

Source: Elaboration on MIUR data, various years.

**Figure 4 – Raw wages by group of field of studies, Italy, 1998-2015**



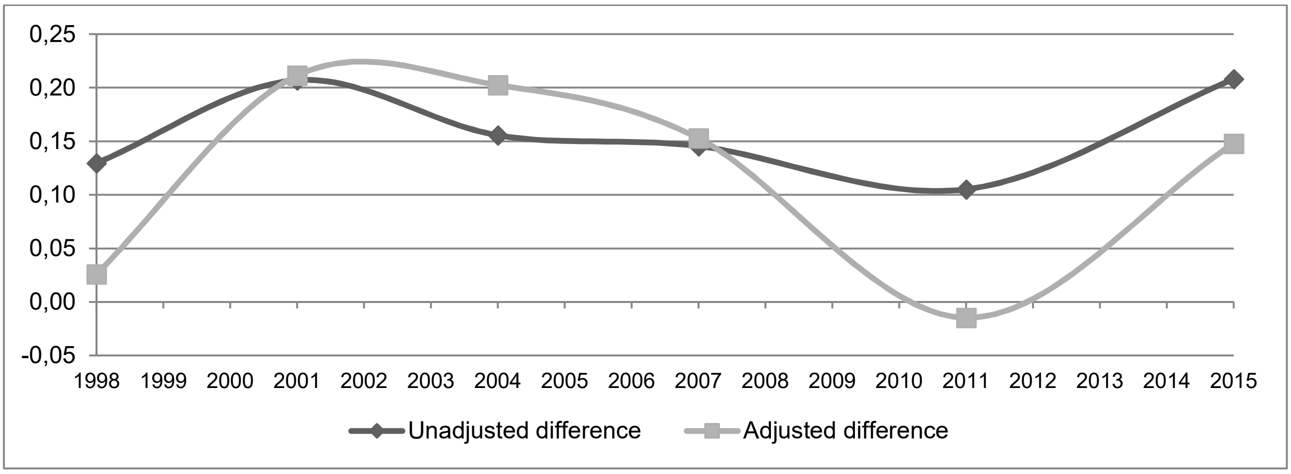

Source: Elaboration on UGS data, ISTAT, various years.

**Figure 5.a – Adjusted and unadjusted wage differences between STEM and Technical-Professionals**



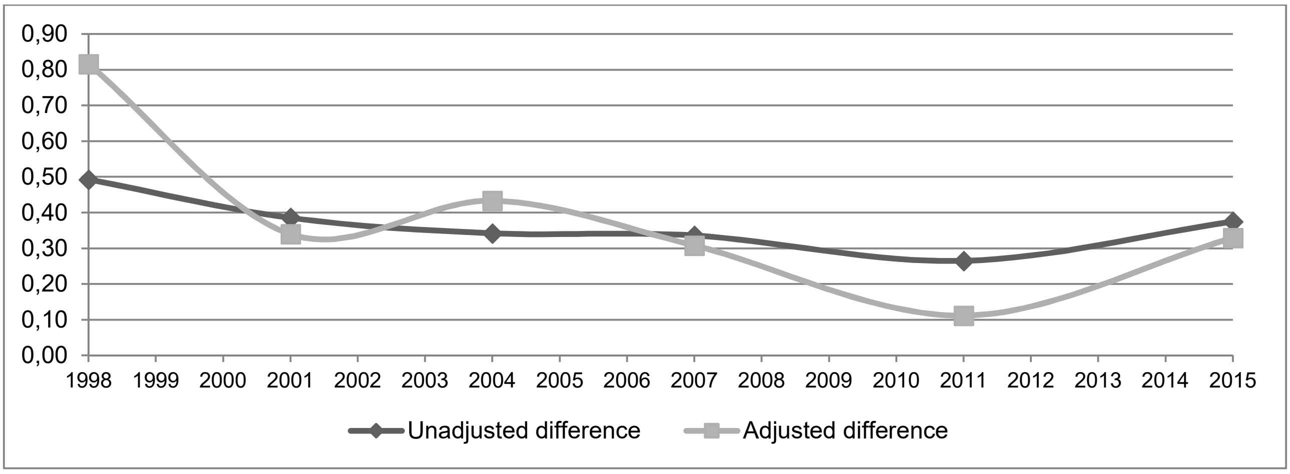

Source: Elaboration on UGS data, ISTAT, various years.

**Figure 5.b – Adjusted and unadjusted wage differences between STEM and Economics&Soc. Sciences**



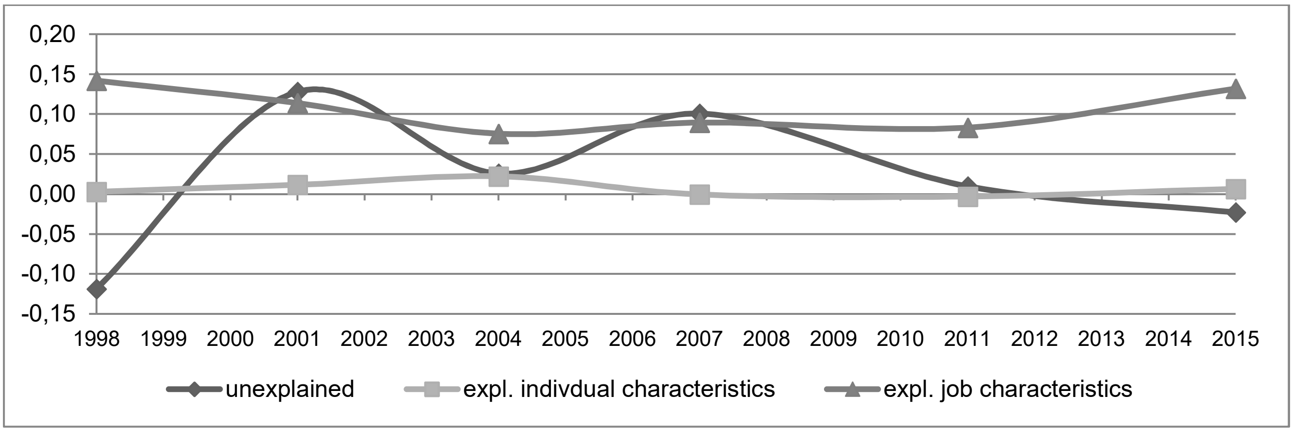

Source: Elaboration on UGS data, ISTAT, various years.

**Figure 5.c – Adjusted and unadjusted wage differences between STEM and Humanities&Teaching**



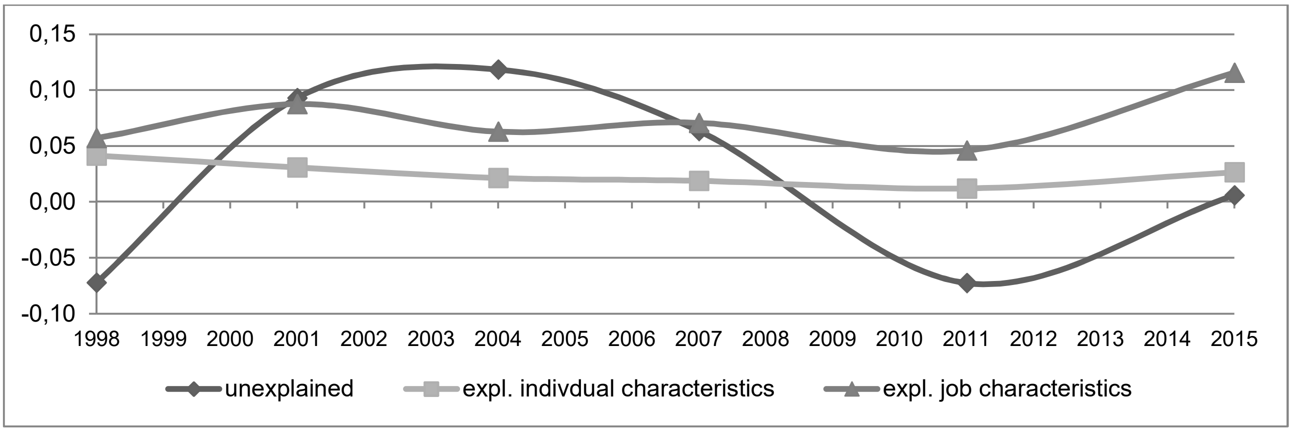

Source: Elaboration on UGS data, ISTAT, various years.

**Figure 6.a – Adjusted wage decomposition between STEM and Technical-Professionals: explained and unexplained part**



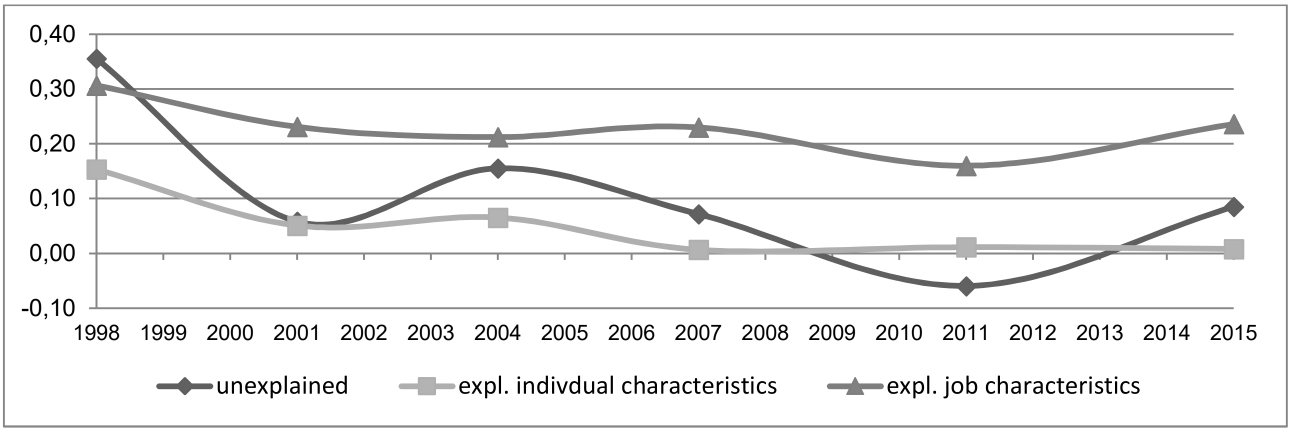

Source: Elaboration on UGS data, ISTAT, various years.

**Figure 6.b – Adjusted wage decomposition between STEM and Economics&Social Sciences: explained and unexplained part**




Source: Elaboration on UGS data, ISTAT, various years.

**Figure 6.c – Adjusted wage decomposition between STEM and Humanities&Teaching: explained and unexplained part**




Source: Elaboration on UGS data, ISTAT, various years.

## Appendix of Tables

### Table A1 – Data and variables description

| VARIABLES | STEM | Technical-Professionals | Economics and Social Sciences | Humanities and Teaching |
|---|---|---|---|---|
| **Social class** | | | | |
| Bourgeoisie | 0.229 | 0.244 | 0.273 | 0.197 |
| Petite Bourgeoisie | 0.156 | 0.186 | 0.173 | 0.189 |
| Middle Class | 0.337 | 0.293 | 0.284 | 0.302 |
| Working Class | 0.279 | 0.276 | 0.271 | 0.312 |
| At least one parent with tertiary degree | 0.279 | 0.257 | 0.253 | 0.215 |
| **School grades** | | | | |
| High-school grade (/100) | 88.892 | 83.165 | 82.922 | 81.219 |
| University grade | 101.647 | 103.828 | 101.523 | 106.669 |
| Degree not in time | 0.735 | 0.692 | 0.696 | 0.674 |
| **Further education** | | | | |
| Yet in education | 0.201 | 0.270 | 0.237 | 0.224 |
| Further education concluded | 0.520 | 0.610 | 0.625 | 0.537 |
| Further education interrupted | 0.047 | 0.050 | 0.051 | 0.043 |
| **Gender**: Female | 0.276 | 0.544 | 0.557 | 0.715 |
| **Type of degree** | | | | |
| Old degree (ciclo unico) | 0.136 | 0.278 | 0.196 | 0.215 |
| First-level degree | 0.429 | 0.428 | 0.485 | 0.464 |
| Second-level degree | 0.436 | 0.293 | 0.318 | 0.321 |
| **Type of occupation** | | | | |
| Legislators, entrepreneurs and Managers | 0.016 | 0.020 | 0.034 | 0.022 |
| Professionals | 0.544 | 0.610 | 0.306 | 0.324 |
| Technicians and Associate Professionals | 0.383 | 0.272 | 0.423 | 0.436 |
| Clerical Support Workers | 0.033 | 0.038 | 0.165 | 0.128 |
| Services and Sales Workers | 0.010 | 0.037 | 0.053 | 0.070 |
| Crafts and Agricultural Workers | 0.005 | 0.011 | 0.003 | 0.007 |
| Plant and Machine Operators | 0.002 | 0.005 | 0.002 | 0.003 |
| Elementary occupations | 0.001 | 0.004 | 0.003 | 0.006 |
| Armed Forces | 0.005 | 0.003 | 0.012 | 0.003 |
| **Branch of economic activity** | | | | |
| Manufacturing | 0.273 | 0.135 | 0.081 | 0.055 |
| Constructions | 0.047 | 0.037 | 0.008 | 0.004 |
| Commerce, Transportation, Hotels and Restaurants | 0.061 | 0.066 | 0.096 | 0.095 |
| Information and Communication | 0.158 | 0.015 | 0.037 | 0.029 |
| Finance | 0.022 | 0.006 | 0.121 | 0.016 |
| Professionals | 0.122 | 0.176 | 0.158 | 0.039 |
| Public Administration, Health, Education and International Organizations | 0.121 | 0.211 | 0.176 | 0.359 |
| Other | 0.197 | 0.355 | 0.324 | 0.387 |
| **Firm Size** | | | | |
| Small firm | 0.397 | 0.680 | 0.539 | 0.593 |
| Medium firm | 0.097 | 0.065 | 0.080 | 0.138 |
| Large firm | 0.506 | 0.255 | 0.381 | 0.268 |
| **Type of contract** | | | | |
| Fixed-term contract | 0.331 | 0.500 | 0.396 | 0.521 |
| Part time | 0.054 | 0.141 | 0.130 | 0.281 |
| Public employment | 0.175 | 0.251 | 0.226 | 0.403 |
| Overeducation | 0.216 | 0.242 | 0.412 | 0.498 |

Source: Elaboration on UGS data, ISTAT, various years. Average values.

**Table A2 –STEM overall earnings gap**

| Years of the Survey | Groups of graduates | Log hourly wages | Working hours per month | Employment rate | STEM overall earnings gap* |
|---|---|---|---|---|---|
| 1998 | STEM | 1.928 | 150.902 | 84.86 | |
| | Technical-Professionals | 1.754 | 139.843 | 71.32 | 29.149 |
| | Economics and Social Sciences | 1.805 | 145.514 | 72.48 | 22.874 |
| | Humanities and Teaching | 1.865 | 119.594 | 68.23 | 38.344 |
| 2001 | STEM | 1.941 | 174.203 | 87.94 | |
| | Technical-Professionals | 1.791 | 165.866 | 77.62 | 22.439 |
| | Economics and Social Sciences | 1.821 | 164.992 | 74.11 | 25.090 |
| | Humanities and Teaching | 1.865 | 142.184 | 75.46 | 32.703 |
| 2004 | STEM | 2.052 | 169.669 | 84.48 | |
| | Technical-Professionals | 1.974 | 163.355 | 76.30 | 16.350 |
| | Economics and Social Sciences | 1.970 | 161.202 | 73.24 | 20.929 |
| | Humanities and Teaching | 2.075 | 134.050 | 78.48 | 25.782 |
| 2007 | STEM | 2.068 | 169.158 | 77.10 | |
| | Technical-Professionals | 1.985 | 161.108 | 68.78 | 18.434 |
| | Economics and Social Sciences | 2.022 | 160.329 | 69.79 | 16.081 |
| | Humanities and Teaching | 2.068 | 133.474 | 74.70 | 23.540 |
| 2011 | STEM | 2.117 | 171.338 | 78.32 | |
| | Technical-Professionals | 2.022 | 164.054 | 67.49 | 21.217 |
| | Economics and Social Sciences | 2.093 | 162.041 | 70.14 | 16.283 |
| | Humanities and Teaching | 2.145 | 135.658 | 72.23 | 26.010 |
| 2015 | STEM | 2.116 | 174.622 | 75.26 | |
| | Technical-Professionals | 1.885 | 162.938 | 64.34 | 28.957 |
| | Economics and Social Sciences | 1.927 | 162.936 | 73.83 | 16.655 |
| | Humanities and Teaching | 2.016 | 131.724 | 74.10 | 29.241 |

$$*SOEG = \frac{(E_S * H_S * ER_S) - (E_j * H_j * ER_j)}{(E_S * H_S * ER_S)} x100 \quad \text{, where:} \quad j = TP, ESS, TH$$

where SOEG means STEM Overall Earnings Gap, $E_s$ is Mean hourly earnings of STEM, $H_s$ is Mean monthly hours paid to STEM, $ER_s$ is the Employment Rate of STEM, $E_j$ are Mean hourly earnings of no-STEM groups, $H_j$ are Mean monthly hours paid to different no-STEM graduates, and $ER_j$ are Employment Rates of no-STEM groups.

**Table A3.a – Estimation results: Oaxaca decomposition between STEM and Technical-professionals**

| Years | 1998 | 2001 | 2004 | 2007 | 2011 | 2015 |
|---|---|---|---|---|---|---|
| **Overall** | | | | | | |
| STEM raw wage | 6.970*** | 7.097*** | 7.143*** | 7.167*** | 7.234*** | 7.369*** |
| Technical-professionals raw wage | 6.741*** | 6.883*** | 7.025*** | 7.009*** | 7.071*** | 7.161*** |
| Difference | 0.229*** | 0.215*** | 0.119*** | 0.157*** | 0.162*** | 0.208*** |
| **Adjusted** | | | | | | |
| STEM adjusted wage | 6.952*** | 7.103*** | 7.157*** | 7.216*** | 7.275*** | 7.368*** |
| Technical-professionals adjusted wage | 6.926*** | 6.850*** | 7.034*** | 7.027*** | 7.185*** | 7.253*** |
| Difference | 0.026 | 0.253*** | 0.123*** | 0.189*** | 0.090** | 0.115** |
| **Explained** | 0.145*** | 0.125*** | 0.097*** | 0.089*** | 0.080*** | 0.138*** |
| **Unexplained** | -0.119 | 0.128** | 0.026 | 0.100* | 0.010 | -0.023 |
| **Explained** | | | | | | |
| Social class | 0.002 | -0.001 | -0.002** | 0.000 | 0.000 | 0.000 |
| At least one parent with tertiary degree | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001* |
| High-school grade | -0.005 | 0.000 | -0.004 | -0.006** | -0.001 | 0.000 |
| University grade | -0.004 | 0.001 | 0.001 | 0.000 | -0.003*** | -0.001 |
| Degree not in time | 0.000 | -0.002** | -0.002** | 0.000 | -0.001* | -0.001** |
| Yet in education | -0.003 | 0.002 | 0.003 | 0.000 | -0.008*** | 0.000 |
| Further education concluded | -0.002 | -0.001 | 0.002** | 0.001** | -0.001 | 0.000 |
| Further education interrupted | -0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Type of degree | | | | | -0.003** | -0.005 |
| Old degree | | | | 0.001 | | |
| Ateneo | | | 0.001 | -0.008*** | 0.001 | 0.003 |
| Female | 0.016 | 0.013*** | 0.023*** | 0.011** | 0.013*** | 0.009*** |
| **Explained individual characteristics** | 0.003 | 0.011 | 0.022 | -0.001 | -0.003 | 0.006 |
| Occupation | 0.001 | 0.000 | -0.002* | 0.001 | 0.004*** | 0.008*** |
| Sector | 0.011 | 0.014*** | 0.012*** | 0.010*** | 0.006** | 0.017*** |
| Firm size | 0.028*** | 0.024*** | 0.012*** | 0.018*** | | |
| Fixed term | 0.024*** | 0.020*** | 0.017*** | 0.013*** | 0.017*** | 0.020*** |
| Part time | 0.074*** | 0.055*** | 0.035*** | 0.045*** | 0.048*** | 0.074*** |
| Public | 0.000 | 0.000 | | | | -0.001 |
| Overeducation | 0.002 | -0.001** | -0.001 | 0.001 | 0.004*** | 0.010 |
| Area of work | 0.001 | 0.002* | 0.003 | 0.001 | 0.003*** | 0.004 |
| **Explained job characteristics** | 0.142 | 0.114 | 0.075 | 0.089 | 0.083 | 0.132 |
| **Unexplained** | | | | | | |
| Social class | -0.001 | -0.001 | -0.004* | -0.001 | -0.001 | 0.004 |
| At least one parent with tertiary degree | 0.009 | 0.004 | -0.004 | -0.003 | 0.003 | -0.004 |
| High-school grade | 0.015 | 0.003 | -0.002 | -0.005 | 0.000 | -0.002 |
| University grade | -0.017 | -0.003 | -0.002 | 0.003 | 0.000 | 0.003 |
| Degree not in time | 0.038 | 0.053** | 0.009 | -0.002 | 0.006 | 0.002 |
| Yet in education | -0.026 | -0.005 | -0.008 | -0.008 | -0.012* | -0.013* |
| Further education concluded | 0.009 | -0.011 | -0.007 | 0.007 | -0.005 | -0.005 |
| Further education interrupted | 0.004 | -0.004** | 0.002 | -0.001 | 0.001 | 0.000 |
| Type of degree | | | | | 0.001* | 0.020*** |
| Old degree | | | | 0.011 | | |
| Ateneo | | | 0.003 | -0.001 | -0.006 | -0.005 |
| Female | -0.053 | -0.019 | 0.009 | 0.010 | -0.004 | -0.001 |
| **Unexplained individual characteristics** | -0.021 | 0.017 | -0.004 | 0.010 | -0.018 | -0.002 |
| Occupation | -0.064* | -0.050 | -0.044 | -0.024 | -0.020 | 0.029 |
| Sector | -0.059** | -0.025** | -0.053*** | -0.011 | -0.014*** | -0.007 |
| Firm size | 0.022** | 0.006 | -0.008* | -0.002 | | |
| Fixed term | -0.017 | 0.001 | 0.017*** | 0.015** | 0.002 | 0.021*** |
| Part time | -0.002 | -0.004 | -0.008** | -0.003 | -0.001 | -0.007** |
| Public | 0.003 | 0.007 | | | | 0.006* |
| Overeducation | 0.002 | 0.008* | -0.001 | 0.015*** | 0.001 | 0.008 |
| Area of work | -0.002 | 0.005 | -0.027 | 0.017* | 0.039 | -0.004 |
| **Constant** | 0.018 | 0.163* | 0.154** | 0.083 | 0.020 | -0.067 |
| **Unexplained job characteristics** | -0.116 | -0.052 | -0.124 | 0.007 | 0.008 | 0.046 |

## Table A3.b – Estimation results: Oaxaca decomposition between STEM and Economics&Social Sc.

| **Years** | **1998** | **2001** | **2004** | **2007** | **2011** | **2015** |
|---|---|---|---|---|---|---|
| **Overall** | | | | | | |
| STEM raw wage | 6.970*** | 7.097*** | 7.143*** | 7.167*** | 7.234*** | 7.369*** |
| Economics&Social Sciences raw wage | 6.840*** | 6.890*** | 6.988*** | 7.021*** | 7.128*** | 7.161*** |
| difference | 0.130*** | 0.207*** | 0.156*** | 0.145*** | 0.105*** | 0.208*** |
| **Adjusted** | | | | | | |
| STEM adjusted wage | 6.911*** | 7.066*** | 7.169*** | 7.216*** | 7.259*** | 7.368*** |
| Economics&Social Sciences adjusted wage | 6.885*** | 6.855*** | 6.967*** | 7.063*** | 7.273*** | 7.220*** |
| Difference | 0.026 | 0.211*** | 0.202*** | 0.153*** | -0.015 | 0.148*** |
| **Explained** | 0.098*** | 0.118*** | 0.084*** | 0.089*** | 0.058*** | 0.142*** |
| **Unexplained** | -0.072 | 0.093** | 0.118** | 0.063* | -0.073*** | 0.006 |
| **Explained** | | | | | | |
| Social class | -0.001 | -0.001 | -0.003*** | -0.001** | 0.000 | 0.000 |
| At least one parent with tertiary degree | 0.000 | 0.000 | 0.000 | 0.000 | 0.001*** | 0.001 |
| High-school grade | 0.006* | 0.005** | 0.000 | 0.002 | 0.003** | 0.002 |
| University grade | 0.000 | -0.007*** | 0.001** | 0.000 | 0.000 | 0.003*** |
| Degree not in time | 0.000 | 0.000 | -0.001* | 0.000 | -0.002*** | -0.002* |
| Yet in education | 0.003 | 0.005*** | -0.001 | -0.001 | -0.010*** | 0.000 |
| Further education concluded | 0.001 | 0.000 | 0.002** | 0.000 | -0.001* | 0.000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Further education interrupted | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Type of degree | | | | | -0.002* | 0.006*** |
| Old degree | | | | -0.001*** | | |
| Ateneo | | | 0.003*** | -0.002 | 0.000 | 0.002 |
| Female | 0.033*** | 0.029*** | 0.020*** | 0.021*** | 0.023*** | 0.014*** |
| **Explained individual characteristics** | 0.041 | 0.031 | 0.021 | 0.019 | 0.012 | 0.026 |
| Occupation | 0.003 | -0.003 | 0.004 | 0.008*** | 0.005** | 0.007* |
| Sector | -0.015** | -0.003 | -0.010*** | -0.009*** | -0.017*** | 0.011*** |
| Firm size | 0.008*** | 0.016*** | 0.009*** | 0.009*** | | |
| Fixed term | 0.010*** | 0.014*** | 0.009*** | 0.007*** | 0.002 | 0.015*** |
| Part time | 0.022*** | 0.047*** | 0.039*** | 0.046*** | 0.047*** | 0.065*** |
| Public | -0.001 | 0.002** | | | | 0.000 |
| Overeducation | 0.028*** | 0.008*** | 0.012*** | 0.010*** | 0.009*** | 0.014*** |
| Area of work | 0.001 | 0.005** | -0.001 | -0.001 | 0.000 | 0.004* |
| **Explained job characteristics** | 0.057 | 0.088 | 0.063 | 0.071 | 0.046 | 0.116 |
| **Unexplained** | | | | | | |
| Social class | -0.001 | 0.000 | -0.001 | -0.001 | -0.002 | -0.001 |
| At least one parent with tertiary degree | -0.006 | 0.010** | 0.006 | 0.007* | -0.004 | 0.000 |
| High-school grade | 0.000 | 0.003 | 0.000 | -0.008* | -0.003 | -0.007 |
| University grade | -0.003 | -0.005* | 0.001 | -0.004 | -0.001 | 0.001 |
| Degree not in time | 0.026 | 0.048** | 0.024 | 0.005 | 0.007 | -0.003 |
| Yet in education | -0.011 | 0.004 | 0.002 | -0.002 | -0.010*** | -0.005 |
| Further education concluded | 0.008 | -0.002 | 0.010 | 0.002 | 0.001 | -0.007 |
| Further education interrupted | 0.003 | -0.005*** | -0.002 | 0.000 | -0.001 | 0.000 |
| Type of degree | | | | | 0.002* | -0.003 |
| Old degree | | | | 0.023** | | |
| Ateneo | | | 0.005 | 0.013*** | 0.007 | 0.001 |
| Female | -0.014 | 0.008 | -0.005 | 0.011 | 0.010* | 0.008 |
| **Unexplained individual characteristics** | 0.001 | 0.061 | 0.039 | 0.044 | 0.006 | -0.016 |
| Occupation | -0.018 | -0.088** | -0.020 | -0.005 | -0.036* | 0.017 |
| Sector | 0.017 | -0.006 | 0.009 | 0.005 | -0.007* | 0.007 |
| Firm size | 0.011 | 0.009* | -0.001 | 0.000 | | |
| Fixed term | 0.000 | 0.005 | 0.004 | 0.005 | 0.006* | 0.024*** |
| Part time | 0.000 | -0.005** | -0.001 | -0.001 | 0.002 | -0.004* |
| Public | -0.001 | -0.004 | | | | -0.003 |
| Overeducation | 0.009 | 0.015*** | -0.010** | 0.005 | -0.007* | 0.006* |
| Area of work | 0.005 | -0.018*** | -0.006 | -0.005 | 0.068*** | -0.016** |
| **Constant** | -0.096 | 0.125** | 0.104* | 0.015 | -0.105*** | -0.011 |
| **Unexplained job characteristics** | 0.022 | -0.093 | -0.025 | 0.005 | 0.027 | 0.033 |

## Table A3.c – Estimation results: Oaxaca decomposition between STEM and Humanities&Teaching

| **Years** | **1998** | **2001** | **2004** | **2007** | **2011** | **2015** |
|---|---|---|---|---|---|---|
| **Overall** | | | | | | |
| STEM raw wage | 6.970*** | 7.097*** | 7.143*** | 7.167*** | 7.234*** | 7.369*** |
| Humanities&Teaching raw wage | 6.478*** | 6.712*** | 6.801*** | 6.831*** | 6.969*** | 6.994*** |
| difference | 0.493*** | 0.385*** | 0.342*** | 0.336*** | 0.265*** | 0.375*** |
| **Adjusted** | | | | | | |
| STEM adjusted wage | 6.946*** | 7.084*** | 7.153*** | 7.207*** | 7.268*** | 7.378*** |
| Humanities&Teaching adjusted wage | 6.130*** | 6.745*** | 6.720*** | 6.899*** | 7.156*** | 7.049*** |
| difference | 0.816*** | 0.340*** | 0.433*** | 0.308*** | 0.112*** | 0.329*** |
| **Explained** | 0.460*** | 0.282*** | 0.278*** | 0.236*** | 0.171*** | 0.244*** |
| **Unexplained** | 0.356** | 0.058* | 0.155** | 0.072 | -0.060* | 0.085* |
| **Explained** | | | | | | |
| Social class | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 |
| At least one parent with tertiary degree | -0.001 | 0.000 | -0.001 | 0.001 | 0.000 | 0.001 |
| High-school grade | 0.010** | 0.006** | 0.007** | -0.002 | 0.003 | 0.001 |
| University grade | 0.004 | -0.010** | -0.002 | -0.003 | -0.009*** | -0.005*** |
| Degree not in time | 0.000 | 0.000 | -0.001 | 0.000 | -0.001 | -0.001 |
| Yet in education | 0.015** | 0.004** | 0.006* | -0.002 | -0.010*** | 0.002 |
| Further education concluded | 0.001 | 0.001 | 0.001 | 0.000 | -0.001 | 0.000 |
| Further education interrupted | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Type of degree | | | | | -0.003** | 0.000 |
| Old degree | | | | 0.000 | | |
| Ateneo | | | 0.005*** | 0.000 | 0.004** | -0.003 |
| Female | 0.122*** | 0.051*** | 0.050*** | 0.013* | 0.028*** | 0.012*** |
| **Explained individual characteristics** | 0.153 | 0.051*** | 0.065 | 0.006 | 0.011 | 0.008 |
| Occupation | 0.026*** | 0.011*** | 0.004 | 0.011*** | 0.007*** | 0.015*** |
| Sector | 0.055*** | 0.072*** | 0.033*** | 0.032*** | 0.015*** | 0.060*** |
| Firm size | 0.045*** | 0.023*** | 0.020*** | 0.023*** | | |
| Fixed term | 0.028*** | 0.022*** | 0.020*** | 0.017*** | 0.022*** | 0.026*** |
| Part time | 0.131*** | 0.114*** | 0.115*** | 0.138*** | 0.107*** | 0.142*** |
| Public | -0.017*** | -0.025*** | | | | -0.024*** |
| Overeducation | 0.019** | 0.008*** | 0.021*** | 0.009*** | 0.006*** | 0.012*** |
| Area of work | 0.020*** | 0.006*** | -0.001 | 0.000 | 0.003*** | 0.006** |
| **Explained job characteristics** | 0.307 | 0.231 | 0.212 | 0.230 | 0.160 | 0.236 |
| **Unexplained** | | | | | | |
| Social class | 0.002 | 0.001 | -0.006** | 0.004** | -0.001 | 0.005* |
| At least one parent with tertiary degree | 0.008 | 0.003 | 0.008 | 0.009 | 0.003 | -0.001 |
| High-school grade | -0.017** | -0.001 | -0.011*** | -0.006 | -0.002 | -0.007 |
| University grade | 0.023 | 0.015 | -0.043 | -0.004 | -0.003 | -0.002 |
| Degree not in time | 0.056 | 0.002 | -0.003 | 0.007 | 0.000 | -0.015** |
| Yet in education | 0.036 | -0.003 | 0.026* | -0.010 | -0.015*** | -0.003 |
| Further education concluded | 0.019 | 0.003 | -0.018 | -0.004 | -0.011* | 0.015 |
| Further education interrupted | 0.001 | -0.003 | -0.004** | 0.001 | 0.000 | 0.001 |
| Type of degree | | | | | 0.001 | 0.020*** |
| Old degree | | | | 0.031** | | |
| Ateneo | | | -0.006 | 0.010 | 0.005 | 0.008 |
| Female | 0.138 | 0.005 | 0.029 | -0.007 | 0.008 | 0.008 |
| **Unexplained individual characteristics** | 0.265 | 0.021 | -0.028 | 0.031 | -0.015 | 0.029 |
| Occupation | -0.054 | -0.073** | 0.011 | -0.015 | -0.019 | 0.037 |
| Sector | -0.033 | -0.022 | -0.014 | 0.002 | -0.020*** | -0.048*** |
| Firm size | 0.007 | 0.015*** | 0.014*** | 0.004 | | |
| Fixed term | -0.025* | -0.008 | -0.002 | -0.019*** | -0.011** | 0.000 |
| Part time | -0.012* | -0.008** | -0.008 | 0.000 | -0.002 | -0.009** |
| Public | -0.023** | -0.016** | | | | -0.005 |
| Overeducation | -0.038** | 0.008 | -0.009 | 0.004 | -0.020*** | -0.002 |
| Area of work | -0.027** | -0.006 | -0.069*** | -0.020* | 0.076** | -0.019** |
| **Constant** | 0.296* | 0.145* | 0.259*** | 0.084 | -0.048 | 0.102* |
| **Unexplained job characteristics** | -0.205 | -0.109 | -0.076 | -0.044 | 0.003 | -0.046 |

## Table A4 – Synthesis of Oaxaca decomposition results: average values 1998-2015

| **Average contribution to wage gaps:** | **STEM-TP** | **STEM-ESS** | **STEM-HT** |
|---|---|---|---|
| *Raw gap* | *0.182* | *0.159* | *0.366* |
| *Adjusted gap* | *0.133* | *0.121* | *0.390* |
| Explained (individual characteristics) | 4.9% | 20.8% | 12.6% |
| Explained (job characteristics) | 79.8% | 60.5% | 58.9% |
| **Total Explained** | **84.7%** | **81.3%** | **71.5%** |
| Unexplained (individual characteristics) | -2.3% | 18.7% | 13.0% |
| Unexplained (job characteristics) | -29.1% | -4.3% | -20.4% |
| Constant | 46.7% | 4.4% | 35.9% |
| **Total Unexplained** | **15.3%** | **18.7%** | **28.5%** |
| *Tot.* | *100.0%* | *100.0%* | *100.0%* |