What drives the wage gap of vulnerable workers? Pay incentives, intangibles and gender wage inequality

Authors:

Cristiano Perugini and Fabrizio Pompei

UNIPG

Deliverable: 4.2

Date: May 2022

This project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 101004776

Abstract

This research focuses on the effects of a managerial practice, Incentive Pay Schemes (IPSs), on the within-firm gender wage gap and explores whether the intensity of investments in intangibles at industry-level moderates the relationship IPS-gender wage gap. To this aim we use establishment level data from the Structure of Earning Surveys (SES), for the years 2006, 2010, 2014 and 2018 and five European countries (Germany, France, Italy, Spain and the UK). Data on intangible capital stocks (on 25 industries) are from EU-KLEMS database. The analysis, which uses econometric methods allowing for potential endogeneity issues, indicates that a higher intensity of IP schemes alleviates the adjusted gender gap. However, this inequality attenuating effect of IPS materialises only in contexts where intangible capital intensity is low. The result is confirmed if, instead of the aggregate intangibles stock, we replicate the analysis in subsamples of firms belonging to industries with high/low intensity of various intangible capital components (Software and Databases; Innovative Property; Economic Competencies; Organisational Capital; Brand expenditures). However, investments in Training emerge as a notable exception; IP schemes reduce the adjusted wage gap even in context of high expenditures in knowledge embedded in firm-specific human capital.

Keywords

Gender pay gap, incentive pay schemes, intangible capital

Acknowledgments

We thank Robert Stehrer from WIIW for having reviewed and having provided comments to an earlier version of this paper. We also thank for their useful comments Ronald Bachmann, Piotr Lewandowski, Wouter Zwysen and all other participants to the Untangled First Expert Workshop on '*Global trends and variations: technological transformations, globalisation, demographics – varieties by regime, region, sector: disruption or reiteration*?' held in Vienna on 25 March 2022.

Please refer to this publication as follows:

Cristiano Perugini, Fabrizio Pompei (2022). *What drives the wage gap of vulnerable workers? Pay incentives, intangibles and gender wage inequality* (Deliverable 4.2). Leuven: UNTANGLED project 1001004776 – H2020.

This project has received funding from the European Union's Horizon 2020 Research and Innovation programme under grant agreement No. 1001004776.

Document control sheet

Project Number:	101004776
Project Acronym:	UNTANGLED
Work-Package:	WP4
Last Version:	
Issue Date:	31/05/2022

Classification

Draft	
Final	X
Confidential	
Restricted	
Public	X

Table of contents

1. Introduction

Gender inequalities, although significantly lower than in the past, still permeate all fields of society in both developed and developing economies. Most of them materialise, directly or indirectly, on the labour market in terms of lower female participation rates, horizontal and vertical segregation and gender wage gaps. An increasing attention in recent years has been devoted to the firm-level sources of wage inequality, particularly related to the effects of wage-setting practices (OECD, 2021). Among them, managerial practices such as incentive pay schemes (IPSs) have played a prominent role. IPSs are primarily intended to improve productivity and boost economic performance of firms, by eliciting more effort from workers (Bloom & Van Reenen, 2007; 2011). At the same time, they tend to increase within-firm wage inequality by setting up compensation systems linked to individual (or group) productivity performances, that are heterogeneous due to specific observable and unobservable characteristics of workers (Gittleman & Pierce, 2015). This is especially the case in contexts where IPSs tend to be implemented more intensively due to the existence of market imperfections. On the side of product market, IPSs can help addressing the various issues related to the distribution of rents (Rusinek & Rycx, 2013); on the labour market side, IPSs can contribute alleviating the inefficiencies due to asymmetric information and high monitoring costs (Lazear, 2000; Marsden & Belfield, 2010).

Previous empirical studies have reported mixed evidence on how IPSs affect gender wage inequality. One strand of the literature maintains that IPSs tend to increase wage disparities, as women are more likely working in firms and positions where incentive-based systems are not implemented or they are less likely than men to receive the bonuses for similar jobs (Zwysen 2021; Arabadjieva & Zwysen, 2022; De La Rica *et al.*, 2015). By contrast, Manning and Saidi (2010) find modest evidence for differential sorting into IPSs by gender and very small, even insignificant, effects of IPSs on hourly wage gaps between men and women.

The main novel contribution of our study is to shed light on the role of IPSs on the gender pay gap once all observable workers, jobs and firm-level characteristics have been controlled for. This means that we look at the residual (or adjusted) wage gap between observationally equivalent male and female workers, employed in the same firm, occupation, and contractual position. In particular, among other things, the gap accounts for differences in skills (proxied by workers' education and occupation) and employment status (temporary or permanent contract). The residual difference in compensations is, therefore, either due to unobservable individual/job factors or to discrimination. A second contribution of our research is to place the analysis within

the debate on the role of investments in intangibles in driving wage disparities. Specifically, we analyse whether the role of IPSs in shaping the gender wage gap is exacerbated or attenuated in industrial contexts characterised by high/low intensity of intangible capital of different types. By focusing on the gender wage gap, we deal with an important segment of the broader category of vulnerable workers, as female employment accounts for the majority of flexible and unsecure jobs, such as those under part-time and temporary contracts.

To our aims, we use establishment-level data from the Structure of Earnings Survey (SES) for the years 2006, 2010, 2014 and 2108 and the five largest European countries (Germany, France, Italy, Spain, and the UK). Firm-level data are then combined with industry-level information on intangible capital stock available in the EU-KLEMS database. Our empirical strategy relies on the estimation of recursive system of simultaneous equations and on control function approaches that allow us to tackle endogeneity and reverse causality issues between our key variable (the implementation and extent of IPSs at firm level) and the adjusted gender pay gap. Our estimation results indicate that firms making a more intensive use of IPSs exhibit a lower (residual) gender wage gap. However, this inequality attenuating effect of IPSs materialises only in contexts less intangible capital intensive. Nonetheless, when we replicate the analysis for different types of intangible capital, we find that IPSs reduce the adjusted wage gap even in contexts of high expenditures in knowledge embedded in firm-specific human and structural resources, i.e.: (a) organisational capital and (b) training. The robustness check performed with the control function approach confirms all findings above, with the only exception of those obtained for organisational capital. We interpret our results in the light of the existing literature on differences in bargaining power, statistical discrimination behaviour of employers, labour organisation models and gender asymmetries in household workloads.

The remainder of the paper is structured as follows. In the next section, we define our research hypotheses on the effects of incentive pay schemes on the adjusted gender wage gap and on the mediating role of intangible capital intensity. Section 3 illustrates the data (3.1) and provides a descriptive analysis of the heterogeneity of the firm-level gender pay and employment gap across countries, sectors and years (3.2). In Section 4, we describe the empirical model and the econometric methods. In Section 5, we present and discuss the estimation results, focusing on the impact of IPSs on the adjusted gender wage gap (Section 5.1); on the heterogeneity of the effects of IPS in context of different intensities of intangible capital of different nature (5.2); and on the robustness of our results (5.3). Section 6 concludes.

2. Incentive pay schemes, intangible capital and gender wage gap: research hypotheses

An increasing attention has been devoted in recent years to the firm-level drivers of wage inequality (Card *et al.*, 2018). In imperfect labour markets, firms can adopt a variety of wage-setting practices shaping a firm-level wage premium that could reflect differences in productivity, rent-sharing, an efficiency wage premium, or strategic wage posting behaviour. When wage premia are asymmetric between groups of workers, they generate heterogeneity of wage gaps between firms (Aghion *et al.* 2018; Cirillo *et al.*, 2017). These firm-specific premia may also explain a relevant part of the wage inequality observed between employees with high/low levels of vulnerability, defined by their individual characteristics or contractual positions. Notably, by including women in the group of vulnerable workers and focusing on gender wage gap, the OECD (2021) pointed out that: (i) about three quarters of the gender pay gap for similarly qualified workers (amounting to 22%) is due to differences in pay within firms; and (ii) a non negligeable portion of this gap is observed for work of equal value, due to statistical discrimination and asymmetries in bargaining power.

The possibility of men enjoying a higher bargaining power compared to equally productive women is also one main explanation of the gender wage gap proposed by Card *et al.* (2016) and Blau and Kahn (2017). A second explanation they provide is related to a between-firm sorting mechanism, due to the gender asymmetries in favour of men in being employed in high paying workplaces.

A complementary strand of literature deals with the effect of incentive pay schemes (IPSs) on the gender wage gap. In general, IPSs are aimed at solving potential moral hazard problems within companies by setting higher wages that elicit the right effort from the workers. If these incentives are only implemented for those workers whose tasks are difficult to monitor, the within-firm wage inequality tends to increase (Lazear & Rosen, 1981; Lazear, 1986; Murphy, 1999). Interestingly, some authors focus on the influence that IPSs may exert on the gender wage gap (Manning & Saidi, 2010; De La Rica *et al.*, 2015; Kato & Kodama, 2018; Zwysen 2021; Arabadjieva & Zwysen, 2022). In principle, if we consider the incentive pay as a component of total compensation determined in a competitive fashion with the aim to increase commitment from the worker's side, equally performing men and women with similar preferences towards risk should receive the same remuneration. This means that an increase in the incidence of the variable pay component on total compensation should reduce the gender wage gap. However, De La Rica *et al.* (2015) enumerate several reasons for which this might not happen. First, the

existence of occupational segregation hinders the access of women to variable pay schemes. This may arise either because the employer practices a statistical discrimination previewing less attachment of women to work due to their responsibilities for housework or because women sort themselves into non IPS jobs, anticipating the statistical discrimination. Second, even when women show preferences like men for IPSs, asymmetries in household work and responsibilities may negatively affect their labour market returns due to a poorer performance related to efforts outside the workplace. Third, firms with monopsonistic power may discriminate women due their limited job mobility and the lack of alternative options in the local labour market. The empirical analysis of De La Rica *et al.* (2015) on Spanish data is consistent with such explanations, showing that the gender gap in performance pay jobs remains fairly high. Other authors offered reviews of recent empirical analyses substantially confirming the explanations above and supporting the view of IPSs widening (or not decreasing) the gender pay gap (Zwysen 2021; Arabadjieva & Zwysen, 2022).

Contrasting evidence is provided by Manning and Saidi (2010) who found, for the UK, modest evidence for differential sorting into IPSs by gender and very small, even insignificant, effects of IPS on hourly wage differentials between men and women. One explanation they give, among others, is that it may be more difficult to discriminate against women under IPSs, where pay and productivity end up more aligned.

Indeed, the impact of IPSs on gender wage gap could be the result of other factors that shape the technological and organisational context in which wage determination takes place. Although direct evidence on the moderating role of technological transformation on the IPS-gender wage gap relationship does not exist, a handful of authors started to wonder whether investments in ICT and intangibles may increase gender inequalities, by increasing returns in job positions where men tend to be overrepresented (e.g. Meyersson Milgrom *et al.*, 2001; Korkeamäki & Kyyrä, 2006). Moreno-Galbis & Wolff (2008) maintain that two contrasting forces shape the relationship between ICT investments and the gender wage gap. On one hand ICTs may contribute shaping a wage premium for men, as digital skills and work experience accumulate less for women who often see their careers interrupted by childcare and other household responsibilities. On the other hand, the novel and automation technologies might have weakened the position that man enjoyed in jobs/sectors in which physical strength granted a comparative advantage, hence narrowing the gender wage gap. The empirical analysis

on these competitive hypotheses, carried out on French workers in 1998 and 2005, is not conclusive as the authors find that the gender wage gap for similar jobs in high ICT intensity industries does not differ substantially from that in low ICT intensity industries.

According to some recent evidence (OECD, 2021), if increasing software investments means more telework implementation, this could help women regaining mobility and improving their outside options in the local labour markets, hence contributing to bridge the wage gap with men. On the other hand, not only women are under-represented in contexts where the digitalisation is more intensive (Segovia-Peréz *et al.*, 2019), but jobs in ICT intensive industries are often characterised by flexible and unpredictable working hour arrangements, that tend to weaken the position of women in the presence of asymmetries in household responsibilities (Goldin, 2014; OECD, 2017; 2019).

In the last thirty years, the literature on technological transformation and knowledge economy pointed out that ICT investments are only one category of a broader group of intangible assets, including innovative property and economic competencies (Corrado *et al.*, 2005; 2009). Innovative property captures all capitalised expenditures on scientific and non-scientific R&D, such as industrial design and development of new products, while economic competencies encompass spending on strategic planning and managing consulting, brand names, and training. Empirical evidence on the effects of these types of investments on gender inequalities is fairly limited. Asplund & Napari (2011) explore the effects of expenditures on R&D (innovative property) and organisational innovations on the gender wage gap within white-collar manufacturing workers and service workers in Finland between 2002 and 2009. They find that the gender pay gap is higher in the service sector and in those industries where investments in the intangible assets considered in the analysis are more pervasive. As underlined recently by the European Commission (2022), one explanation for more severe gender pay gaps in highly innovative environments is related to sorting effects, as women still remain under-represented in sectors, jobs and field of studies where science, engineering or ICT professions play a prominent role. Specifically, the incidence of women among science and engineering and ICT professions was still 25% of total workforce in 2018 and the gender gap in specialist digital skills remains relevant. For this reason, the European Commission is engaged in attracting more women into technology studies and ICT career development. Enhancing digital competences among women by means of training activities is also an important priority in the EU27 (European Commission, 2022).

The aim of our analysis is to contribute to the debate by shedding light on the relationship between IPSs and gender pay gap and on the heterogeneity of this relationship across industries with different intensities of specific intangible capital assets. Based on the discussion just reviewed, our first conjecture is that, once all observable characteristic of workers, jobs and firms are controlled for, it is difficult to argue that the implementation of IPSs can enlarge the (residual) gender wage gap. This gap (observed at firm level) accounts indeed for the part of wage disparities due to unobserved traits of workers (e.g., field of studies, quality of education, tasks within the same occupation/job, preferences for variable pay, innate abilities, family constraints) or to discrimination. Our first research hypothesis *(H1)* is that once potential segregation of women into unsecure and flexible job positions or, more in general, into low productivity firms, is controlled for, a *greater pervasiveness of IPSs in the firm attenuates the gender wage gap* as they: (i) attract not only male, but also female workers with desirable unobserved characteristics and preferences (e.g., high productivity and high risk-propensity women, and those less constrained by household workloads), as they are aware that they can reach the targets and gain a higher remuneration (linked to their performance); (ii) reduce the tendency of employers to resort to statistical discrimination, due to the presence of better screening and monitoring devices implicit in IPSs settings.

However, based on the existing literature, we also acknowledge the fact that the functioning of both mechanisms might be affected by the context in which wage determination takes place, with specific reference to the role of intangible capital assets. In particular, our second research hypothesis *(H2)* is that *some types of intangible investments can inhibit the gender inequality reducing effects of IPSs.* In industries where investments in database and software, innovative property (patents, R&D expenditure) or brands are important, the bargaining power of women could indeed be lower independently on their preferences for bonuses and variable pay. In such technological, knowledge and competitive settings the organisation of labour and working time tends to be extremely flexible and unpredictable; consequently, reconciling work and household responsibilities becomes more challenging, decreasing for them the probability to reach the pecuniary incentives. In addition, in such context, the probability of employers resorting to statistical discrimination is higher, as they anticipate a lower performance of women in jobs less likely to be reconciled with family workloads. By contrast, other types of intangibles may not produce such negative moderating effect. This could be the case for training expenditures, a component of what is normally identified as intangible investment in economic competencies. Firms willing (or needing) to invest more intensively in training are also likely to implement more efficient and developed hiring practices, in view of the specific investment they plan on

their human resources. This more efficient (*ex ante*) screening of the workforce could pose the conditions to resort less to statistical discrimination from the side of employers and to hire women able to compete on an equal ground with their male counterparts. Also, investments in organisational capital, that encompasses expenditures on management consulting and human resource management practices, might improve the implementation of IPSs and through this channel limit the asymmetry of information that mainly drives statistical discrimination and, ultimately, the extent of the (residual) gender wage gap.

3. Data, variables and descriptive evidence

3.1. Data and variables

Our main data source is the Structure of Earnings Survey (SES), a matched employer/employee data set from EUROSTAT. The SES is a large cross-national European survey carried out every four years since 2002. It encompasses workplaces outside agriculture and the public administration which have at least ten employees and gathers detailed data on wages, annual earnings and working time from a sample of workers within those workplaces. The SES is restricted to establishments where the details of at least three workers are observed. This allows for the estimation of averages and spread within the establishment. These data represent a uniquely rich source of information for a consistent comparison of earnings and work-related variables across European economies, extensively used in the literature on labour dynamics and wage inequality in Europe (see, e.g., ILO; 2016; Cirillo *et al.*, 2017; Caliendo *et al.*, 2018; Leythienne & Pérez-Julián, 2021; Zwysen, 2022). Unfortunately, the SES data do not have any longitudinal structure either for workers or workplaces and this poses several empirical constraints. Similarly, balance sheet information to build productivity and other proxies of firm performances are not available. These limitations are offset by the accuracy of harmonised data for a large number of countries and years.

Our analysis is based on data for the years 2006, 2010, 2014 and 2018[1] and covers the four largest EU economies (Germany, France, Italy, Spain) plus the UK. For each country, the data cover a representative sample of firms (stratified by size, sector and geographical area) active in different sectors of activity. For each firm, the data report individual-level information about a representative sample of employees, including wages and a large set of personal and work-related characteristics (age class, gender, education level, tenure, professional occupation, type of contract). The data set also covers a limited set of firm characteristics: the size-class (in terms of number of employees), public vs. private ownership, presence of collective bargaining agreements and the sector of primary activity according to European NACE taxonomy.

Our outcome variable of interest is the within-firm gender wage gap, which can be computed from the wages of the employees sampled in SES within each firm. Based on the seminal work of Winter-Ebmer and Zweimuller (1999) and following Cirillo *et al.* (2017), our approach relies on the use of residual (or adjusted) individual wages to construct an establishment-level gender

[1] Problems related to the coherence in the aggregation of industries due to data anonymisation led us to discard data for 2002.

wage inequality metric. Adjusted individual wages are obtained as the residuals from a standard wage equation, estimated year-by-year and separately for each country, of the type:

$$ln(w)_{ij} = \alpha + \beta Z_{ij} + \theta X_{ij} + \gamma_j + \hat{w}_{ij} \quad (1)$$

Where $(w)_{ij}$ is hourly wage of individual *i* employed in establishment *j;* Z_{ij} is a set of worker's personal characteristics (gender, age, education); X_{ij} is a set of variables describing the worker's job position in establishment *j* (tenure, occupation, type of contract, part/full-time); and γ_j are establishment dummies that provide a measure of the tendency of each establishment to pay high/low wages. The worker-specific residual $\hat{w}_{ij}$ is the part of the individual wage that is not explained by personal and job characteristics or by the general tendency of firms to pay high/low wages. In other words, $\hat{w}_{ij}$ is the component of individual wages that differs between observationally identical individuals who work in the same job and establishment. This residual includes the effects of unobservable workers' characteristics that generate a wage premium/penalty such as: (i) innate abilities/disabilities: (ii) the quality/field of study of education received, which shape higher productivity and/or bargaining power; (iii) preferences for variable pay, which may shape women segregation within firm where bonuses paid are not important. Such preferences might be driven, among other things, by family workloads on which, unfortunately, SES does not provide information. $\hat{w}_{ij}$ can then be used to compute and compare, within each establishment (j), the average adjusted wage for different groups of workers. Hence, our firm-level metric of adjusted gender wage gap reads:

$$\Delta w_j^G = E_j\left(\hat{w}_{ij}^{male}\right) - E_j\left(\hat{w}_{ij}^{female}\right) \quad (2)$$

Where $E_j\left(\hat{w}_{ij}^{male}\right)$ and $E_j\left(\hat{w}_{ij}^{female}\right)$ are the simple averages of the residual wages for male and female workers, respectively. Since computing the gender wage gap within each firm obviously requires a minimum number of employees per group, we restrict our analysis to firms with at least three sampled employees for each gender. Δw_j^G is the firm-level metric used, in the following of the analysis, as the dependent variable in the estimation of the drivers of the within-firm (adjusted) gender pay gap.

Our key explanatory variable for the adjusted gender wage gap is a proxy for the implementation of incentive pay schemes (IPSs). The metric (*av_bonus_share*) is constructed by averaging, across the employees of each firm, the share of bonuses/allowances over the total remunerations paid. To this aim, we use the SES variable B411 (bonuses/allowances not paid in every period) over variable B41 (gross annual earnings). The metric can be seen as a proxy of the

pervasiveness of IPSs at firm level, as it includes the information on both the intensity of extraordinary bonuses/allowances (as a share of individual compensations) and on the spread of bonuses within the firm (by averaging the individual share of bonuses). The existence of industry specificities can bias the variable (e.g., the thirteen month's salary paid to all employees in specific industries, in certain countries); this bias is not a concern for the econometric analysis, as all our regressions include industry fixed effects[2]. Other firm level control variables are firms' tendency to pay high/low wages, size, public/private ownership, collective bargaining, a dummy variable for the presence of female managers, a proxy for innovative activity, and workforce characteristics in terms of average tenure, education, occupation, type of contract.[3]

Lastly, Industry-level data on intangible capital stocks are from the *The EUKLEMS & INTANProd productivity database (February 2022 release)*, maintained by the LUISS Lab of European Economies (https://euklems-intanprod-llee.luiss.it). The database provides capital stock measures for the whole set of intangible assets originally proposed by Corrado *et al.* (2005 and 2009). We use an overall metric of intangible capital intensity (real net capital stock per worker, ppp 2018),[4] measured as the capitalisation of private business spending on intangibles that represents the knowledge capital of the firms. We also consider its three main components:

---

[2] We consider in the analysis the following 25 sectors, that match the EUKLEMS industry data on intangible capital: 1. 'Mining and Quarrying'; 2. 'Food products, beverages and tobacco'; 3. 'Textiles, wearing apparel, leather and related products'; 4. 'Wood and paper products; printing and reproduction of recorded media'; 5. 'Ref. Petroleum, chemicals and pharma'; 6. 'Rubber, plastic and non-metallic mineral products'; 7. 'Basic metals and metal products'; 8. 'Electrical equipment, computer and repair'; 9. 'Machinery'; 10. 'Motor vehicles and other transport equipment'; 11. 'Furniture and other manuf.'; 12. 'Utilities'; 13. 'Construction'; 14. 'Wholesale'; 15. 'Retail trade'; 16. 'Transportation'; 17. 'Accommodation and food services'; 18. 'Publishing and broadcasting activities'; 19. 'Telecommunications, comp. programm. and information'; 20. 'Finance'; 21. 'Real estate, R&D, advert. and other professional activities'; 22. 'Administrative and support services'; 23. 'Education'; 24. 'Health'; 25. 'Community, social and personal services'.

[3] Firm's tendency to pay high/low wages (*firm_wage*) is proxied by (γ_j), the estimated firm fixed effect from equation (1); firm size (*fsize*) is described by three dummy variables for small (less than 50 employees), medium (50-249 employees) and large (over 250 employees) firms. The private/public ownership variable (*public*) is coded 1 if the firm is under public control and zero otherwise; *nocollbarg* is coded as 1 if the firm does not apply any form of collective agreement in wage-setting and zero otherwise; *d_fem_manager* is a dummy variable coded as 1 the firm has at least one female among the employees sampled as managers; *inn_firm* is a dummy variable coded as 1 if the firm has at least one employee in the occupation ISCO 21 'Science and engineering professionals' of the ISCO-08 classification; *av_tenure* is the simple average of the length of service in enterprise (in years) for the firm's employees. The workforce composition is described in terms of firm's shares of female, tertiary educated, part-time, temporary employees, managers (group 1 of the ISCO-08 classification) and high-rank occupation workers (managers, professionals and technicians & associate professionals, corresponding to groups 1-3 of the ISCO-08 classification).

[4] Unfortunately, country-industry level purchasing power parity for this database is not available yet. We use country-level *ppp* for capital goods provided by Eurostat.

(i) database and software; (ii) innovative property (non-scientific and scientific R&D); (iii) economic competencies.[5] The availability of data for the years and countries considered allows further breaking down the third component into: (a) brand names, (b) firm-specific human capital, and (c) organisational structure.[6] A detailed description of all variables used in the empirical analysis is reported in the Appendix (Table A1).

3.2. Descriptive evidence

Table 1 reports the descriptive statistics of the variables used in the analysis. Our sample size amounts to 6,172,766 workers for the estimation of the adjusted individual wages (equation 1), employed in 142,251 companies.[7]

[5] 'Database and software' represent computerised information and reflects knowledge embedded in computer programs and computerised databases. Covers capitalisation of expenses of software and databases developed for a firm's own use; or purchased, and custom software. 'Innovative Property' reflects the scientific knowledge embedded in patents, licenses, and general know-how (not patented) but also the innovative and artistic content in commercial copyrights, licenses, and designs. The category thus encompasses both the 'scientific R&D' and 'non-scientific R&D' components. 'Economic Competencies' represent the value of brand names and other knowledge embedded in firm-specific human and structural resources; it gathers the expenditures designed to raise productivity and profits (other than the software and R&D expenses classified elsewhere).

[6] Spending on brand development is represented by expenditures on advertising and market research and encompasses the costs of launching new products, developing customer lists, and maintaining brand equity. Firm-specific human capital is the incidence and costs of employer-provided training. Investments in organisational change and development have both own account and purchased components. The own-account component is represented by the value of executive time spent on improving the effectiveness of business organisations - that is, the time spent on developing business models and corporate cultures. The purchased component is represented by management consultant fees.

[7] The composition of the sample is strongly biased towards German companies (69,739 units, corresponding to 49% of the total sample); the remaining observations amount to 22,981 for Spain, 22,494 for France, 20,922 for Italy and 6,115 for the UK. The composition of the firm sample by country reflects the composition of the sample of workers and the fact that the SES only includes firms with 10 employees or more. In addition, it is related to the fact that we include in our analysis only companies in which we observe at least three male and three female workers.

Table 1. Descriptive statistics (average 2006-2010-2014-2018)

	Sample		DE		ES		FR		IT		UK	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Firm level variables												
Raw Gender Gap	0.125	*0.211*	0.117	*0.204*	0.131	*0.187*	0.160	*0.234*	0.095	*0.205*	0.158	*0.283*
BS (average bonus share)	0.080	*0.068*	0.053	*0.049*	0.122	*0.079*	0.095	*0.076*	0.116	*0.052*	0.033	*0.053*
sh_female	0.471	*0.200*	0.459	*0.217*	0.489	*0.187*	0.478	*0.182*	0.465	*0.182*	0.525	*0.138*
sh_tert	0.281	*0.291*	0.172	*0.212*	0.383	*0.334*	0.497	*0.309*	0.270	*0.283*	0.332	*0.225*
sh_part	0.255	*0.270*	0.351	*0.289*	0.167	*0.242*	0.138	*0.180*	0.167	*0.207*	0.264	*0.227*
sh_temp	0.122	*0.204*	0.122	*0.183*	0.220	*0.290*	0.060	*0.135*	0.087	*0.174*	0.071	*0.153*
inn_firm	0.156	*0.363*	0.225	*0.418*	0.197	*0.398*	0.007	*0.085*	0.080	*0.271*	0.000	*0.013*
nocollbarg	0.340	*0.474*	0.633	*0.482*	0.067	*0.250*	0.017	*0.128*	0.001	*0.031*	0.482	*0.500*
sh_manager	0.070	*0.146*	0.030	*0.058*	0.039	*0.083*	0.250	*0.260*	0.032	*0.065*	0.120	*0.155*
sh_fem_manager	0.130	*0.286*	0.086	*0.248*	0.088	*0.249*	0.315	*0.329*	0.094	*0.276*	0.245	*0.373*
d_fem_manager	0.212	*0.409*	0.136	*0.343*	0.135	*0.341*	0.584	*0.493*	0.117	*0.322*	0.353	*0.478*
av_tenure	9.143	*5.900*	8.286	*5.637*	9.346	*6.477*	11.43	*5.720*	9.846	*5.670*	7.218	*4.795*
public	0.134	*0.341*	0.067	*0.250*	0.156	*0.363*	0.155	*0.362*	0.265	*0.441*	0.289	*0.453*
fsize (small)	0.250	*0.433*	0.381	*0.486*	0.105	*0.306*	0.082	*0.274*	0.213	*0.409*	0.056	*0.229*
fsize (medium)	0.298	*0.457*	0.318	*0.466*	0.325	*0.468*	0.251	*0.433*	0.326	*0.469*	0.053	*0.224*
fsize (large)	0.452	*0.498*	0.301	*0.459*	0.571	*0.495*	0.667	*0.471*	0.461	*0.499*	0.891	*0.312*
sh_high_occup	0.417	*0.339*	0.335	*0.310*	0.423	*0.356*	0.670	*0.275*	0.395	*0.345*	0.458	*0.292*
Industry level variables (capital stock/worker)												
Intangible K	9.258	*1.197*	8.915	*1.170*	9.396	*1.232*	9.291	*1.361*	9.232	*1.329*	9.455	*0.989*
Software & Database	7.682	*1.335*	6.701	*1.086*	7.798	*1.495*	8.074	*1.235*	7.755	*1.315*	8.160	*1.080*
Innovative Property	8.608	*1.474*	8.527	*1.535*	9.074	*1.318*	8.491	*1.726*	8.891	*1.229*	8.410	*1.408*
Economic Competencies	8.249	*1.570*	8.173	*1.157*	7.167	*2.374*	8.674	*1.008*	7.526	*1.680*	8.967	*0.966*
Brand	7.342	*1.332*	6.809	*1.231*	7.508	*1.184*	6.829	*1.573*	7.300	*1.429*	7.924	*0.991*
Organisational capital	8.217	*0.967*	7.754	*0.960*	7.687	*0.854*	8.682	*0.995*	8.164	*0.717*	8.612	*0.830*
Training	7.380	*0.912*	7.421	*0.644*	6.835	*1.264*	7.471	*0.824*	7.447	*0.871*	7.522	*0.858*

Source: Own elaborations from SES and EU-KLEMS data

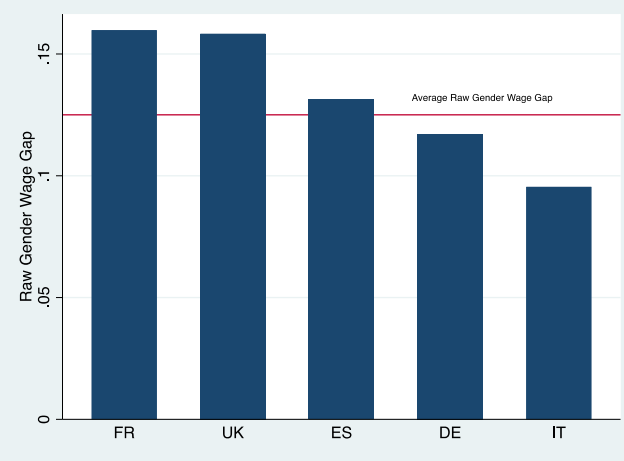
As for the two main firm-level dimensions of gender inequality, firms in our sample pay female workers, on average, 12.5% less than their male counterparts, with remarkable differences between countries: the firm-level average gender pay gap ranges indeed from 16% in the UK to 9.5% in Italy (see also the top-left panel in Figure 1). This heterogeneity only partly reflects the differences in wage gaps across countries calculated on workers; for example, the gap is significantly higher in Germany (19%), since firms with higher gender gaps are on average of a larger size.[8] The gender gap shows a decreasing tend over the period considered (bottom-left panel in Figure 1). The firm level raw gender gap is highly and significantly correlated (76%, significant

[8] The raw gender gaps calculated on workers amount to 19% for Germany; 17% for France and Spain, 16% for the UK and 6% for Italy.

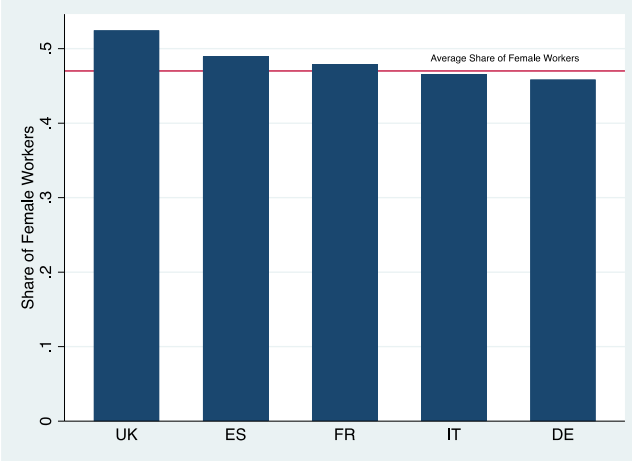
a 1%) to the adjuster gap computed as in equation (2). This means that the residual gap reflects the raw differences but also adds some important information that would not be visible in the unadjusted measure. On average, female workers account for 47% of the workforce of the firms of our sample, and the share ranges from 52% in the UK to 46% in Germany and Italy; the trend of the female employment share over time is virtually flat, with a temporary decline in the year 2010 (right-hand panels of Figure 1).

Figure 1. Average firm level gender wage and employment differences across countries and over time

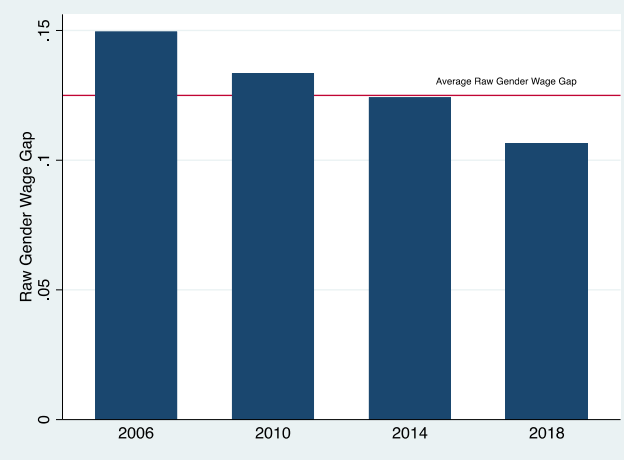
Raw Gender Pay Gap by Country



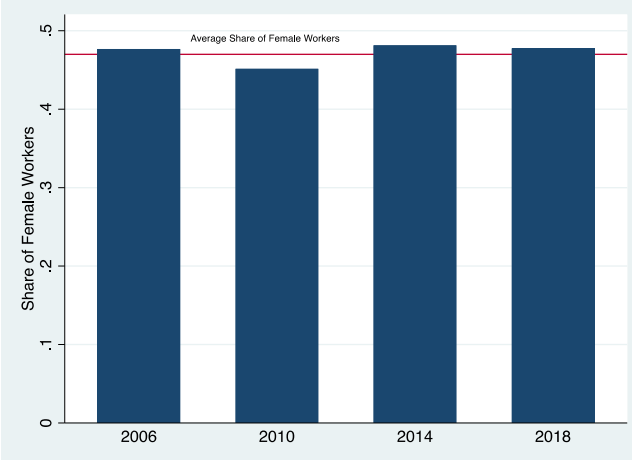
Share of Female Workers by Country



Raw Gender Pay Gap by Year



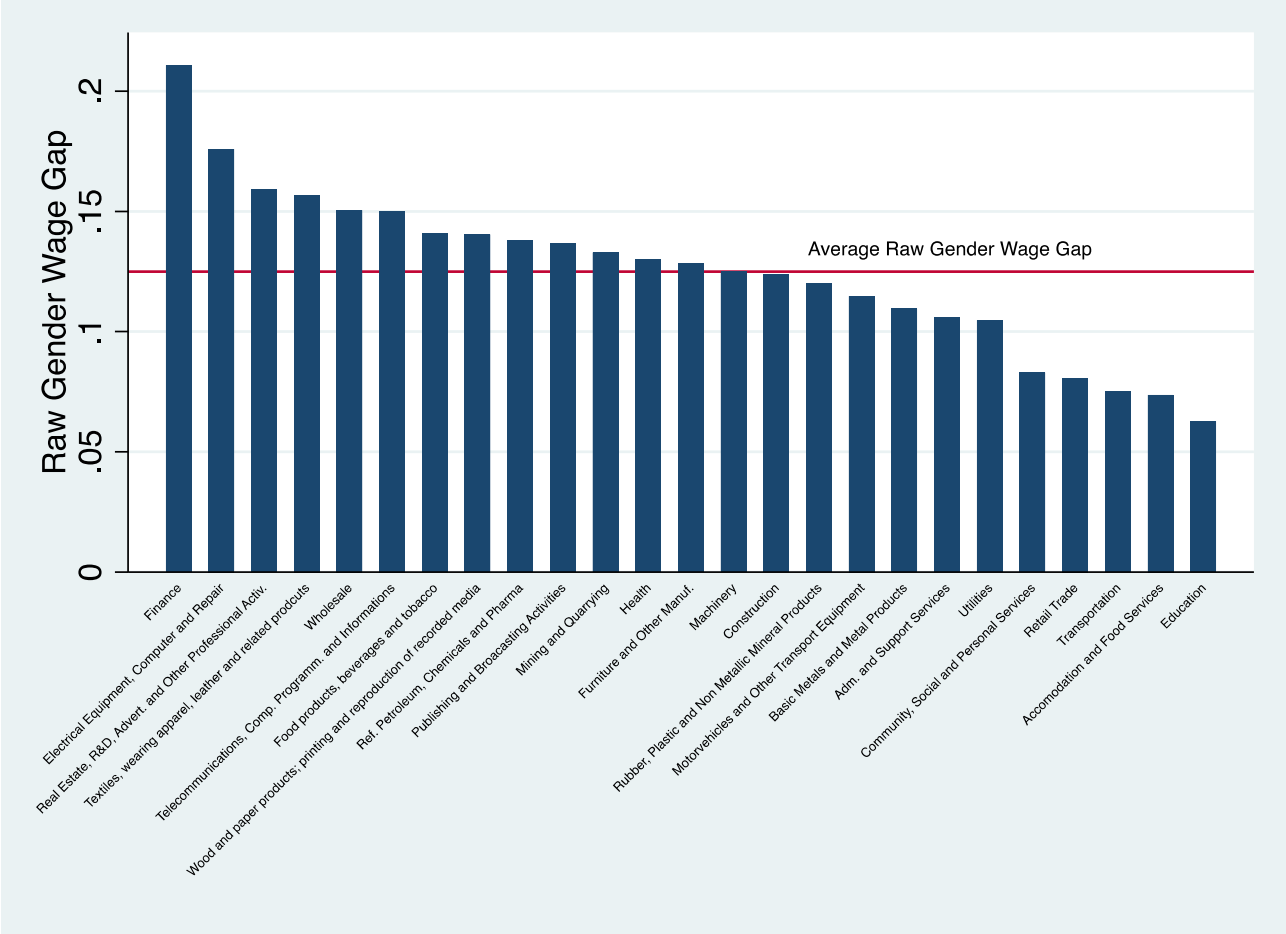
Share of Female Workers by Year



Source: Own elaborations from SES data

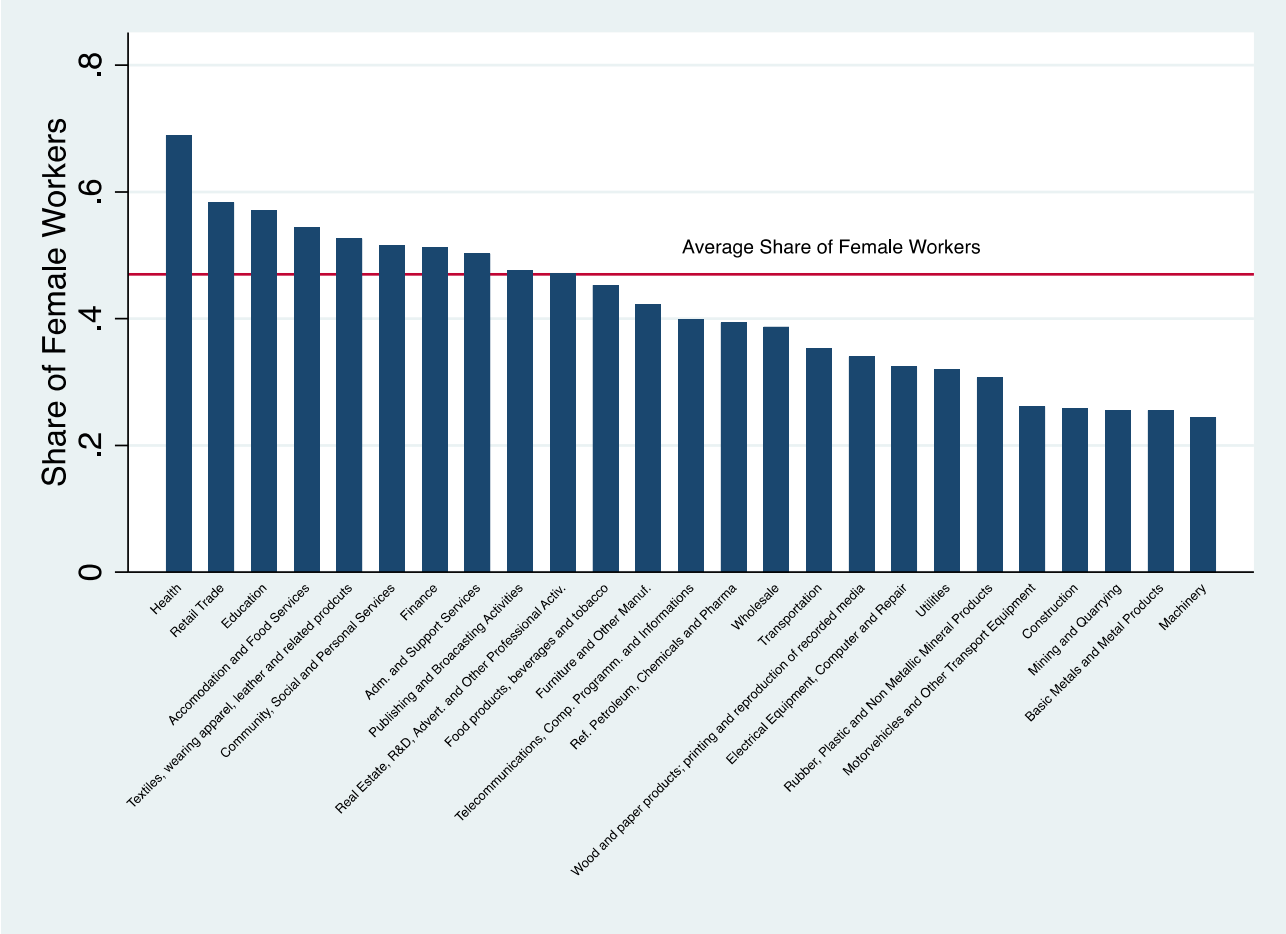
The plots of gender inequality across industries (Figures 2 and 3) reveal a remarkable heterogeneity of gender pay inequality (ranging from over 20% in the financial sector to 6% of education) and confirm a well-known pattern of horizontal segregation of the female workforce into specific services such as health, retail trade and education (Eurofound, 2021) and manufacturing branches (textile products).

Figure 2. Average firm level gender wage gap across industries



Source: Own elaborations from SES data

Figure 3. Average firm level employment gap across industries



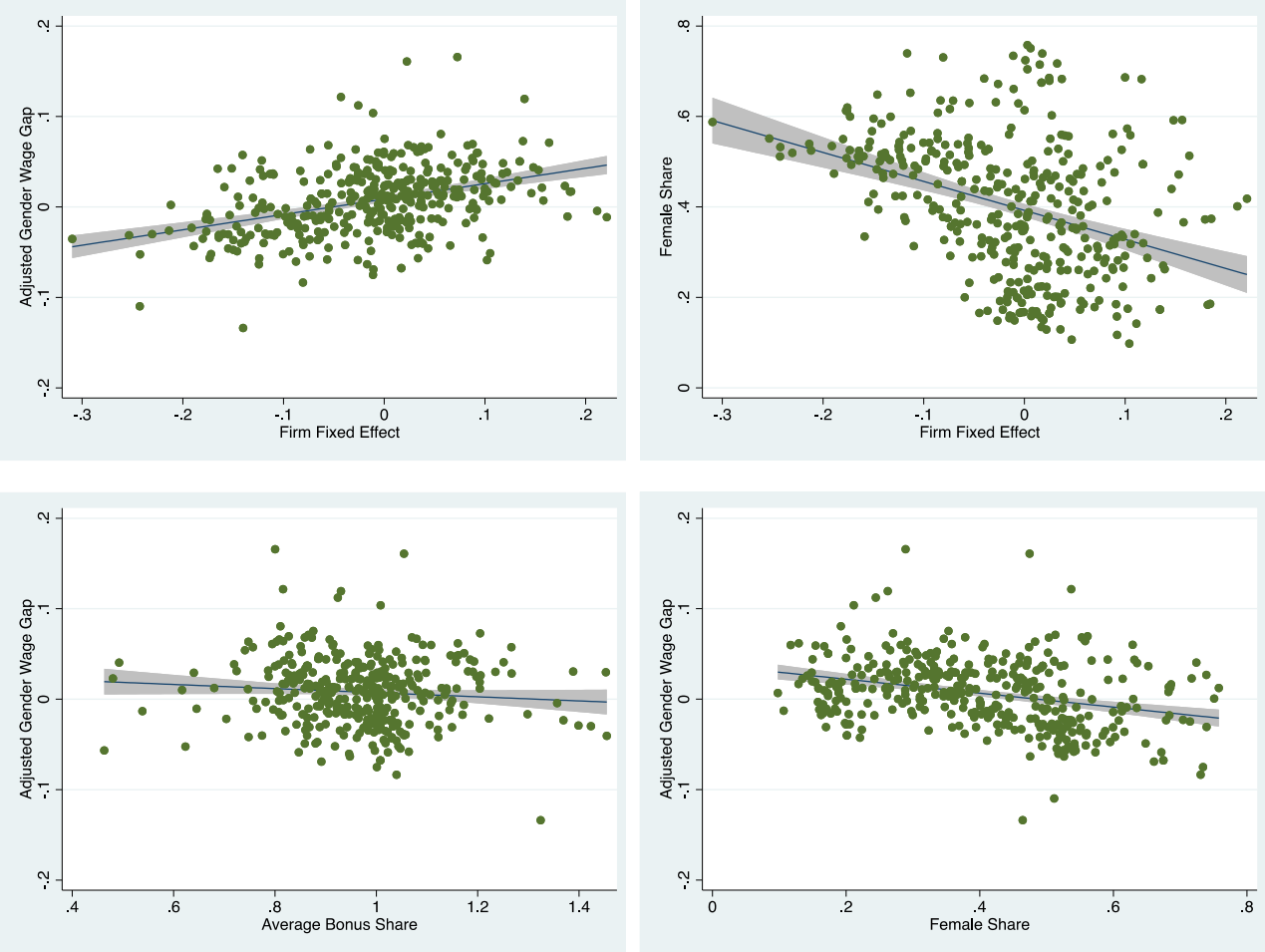
Source: Own elaborations from SES data

Other firm-level statistics reported in Table 1 reveal a high heterogeneity between the countries considered in virtually all domains. To the specific aims of our research, it is noteworthy the high variability in the incidence of part-time and temporary jobs and in the share of tertiary educated employees. However, if we look at the distribution by gender of such shares we find, with the partial exception of the UK, remarkable asymmetries (see Table A2 in the appendix). Female workers are everywhere proportionally more employed in the employment segments associated to higher vulnerability (temporary or part-time jobs); in Germany and France the share of women holding a tertiary education is lower than the share of men, whereas the contrary holds in the remaining countries.

Figure 4 provides a first snapshot of the relations between some key variables on which our research is focused, using data averaged over country, time and industry. The two top panels highlight that the sectors with a propensity to pay higher wages (average γ_j is on the horizontal

axis) tend to exhibit a stronger gender inequality in both compensations and workforce composition.

Figure 4. Gender differences, propensity to pay high wages and to implement IPS (firm level averages across country/time and industry)

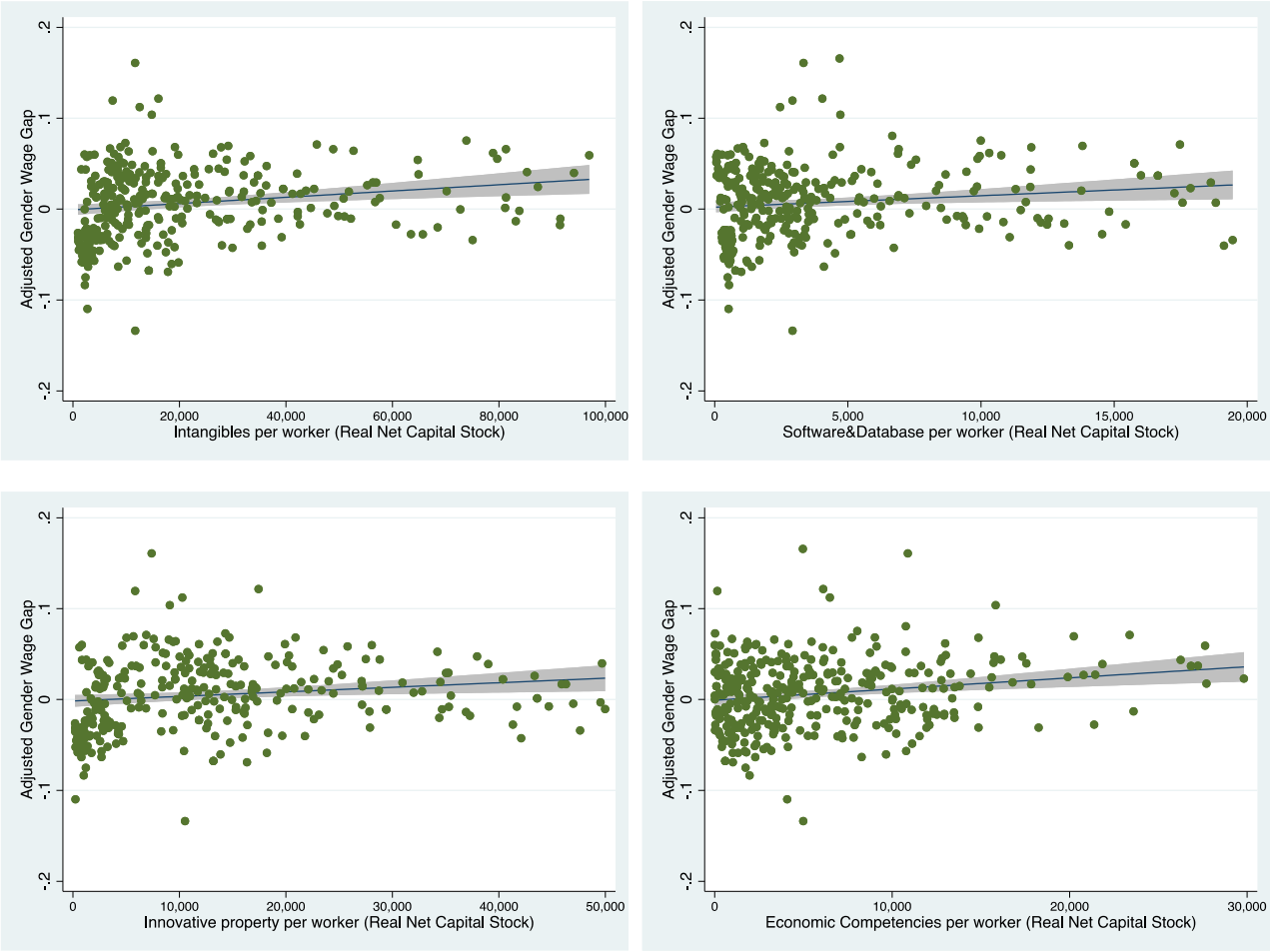


Source: Own elaborations from SES data

Although less graphically apparent, a negative correlation also emerges between the adjusted wage gap and the female employment share (bottom-right panel of Figure 4) on one hand and the average bonus share (BS) on the other (bottom-left panel). This is a first empirical piece of evidence corroborating our conjecture on the possible attenuating role played by IPS on gender pay inequality.

To conclude this descriptive overview, we plot in Figure 5 the relation between industry/country/year averages of firm's adjusted gender wage gap and the intensity of intangible capital. For the aggregate intangible capital measure and for all its components, we observe deeper levels of inequality in industrial contexts in which intangible capital is more pervasive.

Figure 5. Gender differences (firm level averages across country/time and industry) and intangible capital intensity



Source: Own elaborations from SES data

4. Empirical methods

The investigation of the effects of incentive pay schemes (IPS) on the gender gap poses several identification challenges, due to endogeneity/reverse causality issues. For our aims, two potential identification challenges are of particular concern.

The first one refers to the potential endogeneity of the strength of IPS to gender inequality, as it is possible that some omitted variables such as practices of statistical discrimination exerted by employers (De La Rica *et al.*, 2015), are simultaneously correlated to the gender wage gap and average bonus. A *reverse causality-based* endogeneity is also possible; for example, in contexts where gender discrimination is stronger it could be more difficult to implement incentive pay schemes, as: (a) firms less committed to equity/equality and social sustainability in general, or with less flexible work arrangements, are usually characterised by more traditional human resources management styles, that only marginally rely on the measurement of performance and incentive-based compensations (Marsden and Belfield, 2010); (b) in the presence of discriminatory practices the perception of fairness is low and conflictual relations between workers and management are likely to prevail over cooperative behaviours, which are normally the pre-condition for setting up and agreeing on incentive-based pay schemes (Cruz *et al.*, 2011).

The second identification issue is related to the interaction of two main dimensions of gender inequality, related to gender asymmetries in remunerations (the pay gap, focus of our analysis) and in employment (unbalanced gender distribution of workers within firms and occupations). The inclusion of the share of female employment among the drivers of the adjusted gender wage gap is important, as it accounts for the fact that in firms where employment is more balanced, discriminatory practices tend to be more difficult to implement. However, the reverse direction of causality is also plausible, as more (pay) discriminatory contexts tend to attract less women. Even more importantly, the implementation of IPS can also affect the gender composition of the firm's workforce since, as shown by the existing evidence, in the presence of asymmetric housework burdens, women are less attracted by firms implementing performance pay schemes because they are less likely to be able to compete successfully for the bonuses (Biasi & Sarsons, 2022, Arabadjieva & Zwysen, 2022; Zwysen 2021; Card *et al.*, 2016; De La Rica *et al.*, 2015, among many others).

To deal with the complexity of such interactions in the empirical model, we rely on the estimation of a system of simultaneous equations (see Zellner & Theil, 1962), where some equations include endogenous explanatory variables that are dependent variables from other equations in the system. All the three dependent variables we consider (adjusted gender wage gap, share

of female workers and average bonus share) are therefore explicitly taken to be endogenous to the system and are treated as correlated with the disturbances in the system's equations. At the same time, the inclusion of specific drivers (excluded instruments) for the share of female workers and for the average bonus share allows the construction of a set of recursive equations as in two stage least square (Roodman, 2011). All other (control) variables in the system are treated as exogenous to the system as well and uncorrelated with the disturbances; as such, they are included as instruments for the endogenous variables.

Formally, we define the recursive system of equations for the three endogenous variables as:

$$\Delta w^{G}_{jrsct} = \beta_1 BS_{jrsct} + \beta_2 \hat{\gamma}_{jrsct} + \beta_3 Fem\_Sh_{jrsct} + \boldsymbol{V}'_{jrsct}\,\boldsymbol{\beta}_4 + \rho_r + \mu_s + \eta_c + \nu_t + I_{ct} + \varepsilon^1_{jrsct} \tag{3.1}$$

$$\begin{aligned} Fem\_Sh_{jrsct} = {} & \zeta_1 BS_{jrsct} + \zeta_2 \hat{\gamma}_{jrsct} \\ & + \zeta_3 Tert\_Sh_{jrsct} + \zeta_4 Part\_Sh_{jrsct} + \zeta_5 Temp\_Sh_{jrsct} + \boldsymbol{V}'_{jrsct}\,\boldsymbol{\zeta}_6 + \rho_r + \mu_s + \eta_c \\ & + \nu_t + I_{ct} + \varepsilon^2_{jsct} \end{aligned} \tag{3.2}$$

$$\begin{aligned} BS_{jrsct} = {} & \gamma_1 Inn_{jrsct} + \gamma_2 No\_coll\_barg_{jrsct} + \gamma_3 Manag\_Sh_{jrsct} + \boldsymbol{V}'_{jrsct}\,\boldsymbol{\gamma}_4 + \rho_r + \mu_s + \eta_c \\ & + \nu_t + I_{ct} + \varepsilon^3_{jsct} \end{aligned} \tag{3.3}$$

Where: Δw^{G}_{jrsct} is the adjusted gender wage gap in firm *j*, region *r*, sector *s*, country *c* and year *t* (from equation 2); Fem_Sh_{jrsct} is the share of women in the (observed) workforce of the firm; BS_{jrsct} is the average bonus share in the firm (proxy of IPSs); $\hat{\gamma}_{jrsct}$ is the propensity of the firm to pay high/low wages (from equation 1); V is a vector of control variables common to all equations;[9] ρ_r , μ_s , η_c, ν_t, are region, industry, country, year fixed effects, respectively; I_{ct} is an interaction between country and year fixed effects capturing all country-level institutional changes occurred between 2006 and 2018. Our main equation of interest is equation (3.1) which, besides the set of controls V common to all equations, includes firms' propensity to pay high/low wages and the two dependent variables of equations (3.2) and (3.3), i.e., Fem_Sh_{jrsct} and BS_{jrsct}. Each of the two equations includes in the set of regressors specific drivers based on

[9] The vector includes firm size dummies (*fsize*), the private/public ownership variable (*public*), the presence of female managers (*d_fem_manager)* the average tenure of employees (*av_tenure)* and the share of high-rank occupation workers (*s_high_occup*).

the available literature. As for Fem_Sh_{jrsct}, we included the shares of tertiary educated employees, of part-timers and temporary workers, all normally associated to higher female employment shares (OECD, 2021; Ponzellini *et al.*, 2010). We also included the IPSs proxy (BS_{jrsct}) since, as already explained, the presence of incentive pay systems can discourage women employment in the firm. As for the BS_{jrsct} equation, we include as specific regressors: (a) the innovation dummy, as we expect IPSs to be more intensively used in high-innovative contexts characterised by uncertainty and informational complexity, where taking full advantage of the employees' potential is crucial to the success of the company (Marsden & Belfield, 2010); (b) the dummy indicating the absence of any kind of collective bargaining, which is likely to provide higher flexibility to human resource management and pay policy design; and (c) the share of managers in the firm, as IPSs are usually more common for management positions and the presence of managers tend to be relatively higher in non-family owned firms, where monitoring and informational problems are more stringent and the implementation of incentive pay schemes more needed (Barth *et al.*, 2005; Bloom & Van Reenen, 2007). Through the estimation of the recursive system, we are able to model at the same time the direct effect of IPS on the gender pay gap (equation 3.1) and its indirect effect through the gender composition of the workforce (equation 3.2).

The estimation of equations 3.1-3.3 relies on Maximum Likelihood (ML) methods. Specifically, we use a ML-SUR model based on simultaneous and recursive equations system where endogenous variables can feature in one another's equations and allow for the substantial simultaneity between the three dependent variables (see Roodman, 2011, also for the Stata routine *cmp* used). To take possible correlation of errors within firms, standard errors are clustered in all estimations at the industry/country/year/ region.

The analysis of the heterogeneity of the effects of IPS in context of different intensities of intangible capital is based on a split sample analysis for subsamples of firms belonging to industries

with intangible capital intensity above/below the median of the distribution of all sectors in all years.[10]

To test the robustness of our results, we replicate the baseline and the split sample estimations using an instrumental variable (IV) specification implemented as a control function approach (Wooldridge, 2015; Aghelmaleki *et al.* 2021; Lewandowski *et al.*, 2022), using as instrumental variables the equation specific regressors described for equation (3.2) and (3.3).[11] The two-step control function procedure is simply based on three OLS regressions. In the first step, the two endogenous variables (average bonus share and share of female workers) are regressed on included and excluded instruments, as described with reference to equations 3.2 and 3.3. In the second step, residuals obtained from the first stage regressions ($\hat{\varepsilon}^2_{jsct}$ and $\hat{\varepsilon}^3_{jsct}$) are included as control variables in the main equation (3.1) to eliminate endogeneity. Compared to the classical 2SLS approach, the control function approach allows obtaining a heteroskedasticity-robust Hausman test of the null hypothesis that the estimated parameters of residuals are significantly different from zero. This guarantees that the two explanatory variables of interest are actually endogenous (Wooldridge, 2015). To obtain proper standard errors in the second stage, a boot-strapping procedure has been implemented.

[10] Table A3 in the appendix reports a summary of industries most frequently falling in these two groups for total intangible capital and its components. As expected, traditional manufacturing and service industries are predominantly classified as low (total) intangible capital per worker sectors (textiles, wood and paper, basic metals, wholesale, retail trade and transportation). However, there are notable exceptions, such as the food industry, that falls in the group of high intensity of intangible capital per worker. This result is driven by economic competencies and more in particular by its brand expenditures sub-component. In more general terms, it is not negligible the number of industries for which economic competencies and its sub-components (organisational capital, brand expenditures and training) do not follow the overall pattern depicted by total intangibles. This also holds for differences between software & database and innovative property. For this reason, a split sample analysis on different categories of intangible capital is a promising option.

[11] Severe heteroskedasticity may indeed significantly affect the consistency, and not only the efficiency, of the estimated parameters with ML-SUR model.

5. Results: IPSs and the adjusted gender wage gap

5.1. Baseline results

Table 2 illustrates the results of the baseline estimation of the system of equations 3.1, 3.2 and 3.3, in which simultaneity among the three dependent variables (adjusted gender wage gap, share of female workers and average bonus share) is accounted for. The estimation is based on the total sample, pooling all firms in the five countries, four points in time and twenty-five industries considered. The use of instruments in equations 3.2 and 3.3 allows the construction of a set of recursive equations as in two stage least square (Roodman, 2011). In our case, the second stage describes the relationship of our core interest and reveals that a more pervasive implementation of IPSs is associated to a lower adjusted gender wage gap (first column of Table 2, equation 3.1), once we control for the factors explaining gender asymmetries in the firm's workforce (column 2, equation 3.2) and for specific determinants of average bonus share (column 3, equation 3.3). More in detail, a one percentage point increase in the incidence of bonus on the yearly wage reduces the adjusted gap by 0.56 percentage points. This baseline result corroborates our first research hypothesis (H1) and, as conjectured in section 2, can be explained in the light of the metric of gender wage gap used, which describes the part of gender inequality unexplained by all observable worker, employer and job characteristics. In addition, we account for the factors that can explain the segregation of women in certain jobs, probably due to gender asymmetries in housework (De La Rica *et al.*, 2015). Indeed, column 2 shows that, overall, women concentrate in those workplaces with lower propensity to pay higher wages (the coefficient for *firm_fe* is negative and significant) and where the incidence of part-time and temporary contracts, more suitable to reconcile work and family tasks, is higher (*sh_part* and *sh_temp* are both positive and significant). Similarly, from column 2 we learn about a sorting effect for women in those companies where the implementation of variable pay schemes is less pervasive: a one percentage point increase in the average bonus share reduces the share of women in the company workforce by -1.14 percentage points.

Results illustrated in column 3 of Table 2 suggest that the implementation of IPSs is related to specific firms' characteristics. IPSs are more frequently implemented in innovative and managerial firms (*inn_firm* and *sh_manager* are both positive and significant), where incentivising workers' performance is vital to the firm's success and the complexity of tasks makes monitoring particularly difficult (Marsden & Belfield, 2010). It is also worth noting that the presence and strength of incentive pays is positively related to the presence of collective bargaining mechanisms (negative and significant coefficient for *nocollbarg*, the dummy variable indicating

the absence of any form of collective wage negotiations). This is consistent with the evidence that some forms of collective bargaining, e.g., the highly decentralised (company-level) mechanisms, have gained increasing attention across Europe in the last years as measures able to realign wages and productivity (Bryson *et al.*, 2012).

As for the control variables included in equation 3.1 (column 1), results are consistent with the recent evidence on the drivers of the gender pay gap and can be interpreted as a sign that our model is correctly specified. For example, it is well known that the gender wage gap widens in companies where job tenure is more important (*av_tenure*) and the share of high-pay occupations (*sh_high_occup*) is higher (Eurofound, 2021). Conversely, the gap is narrower in state-owned companies (*public)*, where wage distributions tend to be more compressed and discriminatory behaviours on wages are more difficult (Ponzellini *et al.*, 2010, p. 12). The pro wage inequality effect of the presence of female managers, although very small in magnitude, is in line with the *'queen bee'* theory, according to which women in leadership positions oppose initiatives to tackle gender inequality because they have to distance themselves from feminine issues in order to justify and secure their position (Van Hek & Van Der Lippe, 2019; Derks *et al.*, 2016).[12]

[12] This result is much more nuanced than it appears if we take all outcomes from our system of equations into account. The presence of female managers also indirectly contributes to narrowing the gender wage gap, as it favours both the implementation of IPSs (column 3) and a higher share of female workers (column 2).

Table 2. Baseline estimations: the effects of IPS on the adjusted gender wage gap

	(1) Adjusted gender wage gap	(3) Share of female workers	(3) Average bonus share
BS (average bonus share)	-0.564***	-1.136***	
	(0.148)	(0.203)	
firm_fe (γ)	0.061***	-0.035***	
	(0.005)	(0.006)	
sh_female	-0.159***		
	(0.018)		
sh_tert		0.007	
		(0.005)	
sh_part		0.229***	
		(0.009)	
sh_temp		0.014***	
		(0.005)	
inn_firm			0.009***
			(0.001)
nocollbarg			-0.012***
			(0.001)
sh_manager			0.035***
			(0.004)
d_fem_manager	0.007***	0.056***	0.004***
	(0.002)	(0.002)	(0.001)
av_tenure	0.001***	0.003***	0.002***
	(0.000)	(0.001)	(0.000)
public	-0.011***	0.020***	-0.007***
	(0.003)	(0.004)	(0.001)
fsize (medium)	0.004	0.010***	0.011***
	(0.002)	(0.003)	(0.001)
fsize (large)	-0.001	0.015***	0.020***
	(0.004)	(0.005)	(0.001)
sh_high_occup	0.023***	0.034***	0.025***
	(0.006)	(0.008)	(0.001)
Constant	0.109***	0.344***	0.065***
	(0.022)	(0.019)	(0.005)
Year/country/region/ industries dummies	Yes	Yes	Yes
Observations	142,251	142,251	142,251

Notes: Standard errors, clustered at industry/country/year/ region, are reported in parentheses. All equations include region, industry, country, year and country*year effects.
***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

To sum up, our baseline outcomes indicate that, after approximating the mediating effect of sorting of female workers in less productive firms that do not resort to variable pay (indirect effects of bonus and propensity to pay higher wages mediated by the share of female workers in column 2), a higher intensity of IP schemes alleviates the adjusted gender gap. As hypothesised in H1 (see Section 2), this probably happens because female workers with unobservable individual and household characteristics similar to their male high-performance counterparts tend to be attracted by such pay systems able to reward their high potential. At the same time, employers resort less to statistical discrimination, due to the presence of better screening and monitoring devices implicit in IPSs.

5.2. Split sample analysis over industries with high/low intensity of intangible capital

Our second research hypothesis (H2) maintains that the positive role played by IPSs on the adjusted gender wage gap might be shaped by a different intensity of intangible capital. Specifically, higher investments in certain intangible assets contribute forging high-innovative business practices and workplace organisation that require highly flexible and unpredictable working time; in such contexts, even for women with unobserved preferences towards variable pay, taking advantage of the opportunities offered by the IPSs might become problematic.

Tables 3 and 4 summarise the results of the split sample analysis, in which the same three-equations model as in Table 1 is estimated for subsamples of firms operating in industries with high/low intensity of intangibles stock per worker.

High- and low-intensity intangibles sectors in each year are identified as those with an intangible stock per worker above and below the median of the distribution of all sectors, years, and countries. To investigate upon our hypothesis H2, we start by breaking down intangible capital in its three main components, that is, software and database, innovative property (R&D expenditure, patents, industrial design) and economic competencies (Table 3). Similarly, data availability on the components of the third aggregate - economic competencies - allow splitting the analysis into brand expenditures, organisational capital and training (Table 4). To make the core results more readable, we only report in Tables 3 and 4 a summary of results for the main equation (3.1); detailed results for all equations and variables are available in the Appendix (Tables A4-A10). A graphical summary of the magnitude of the IPSs coefficients (average bonus share) and their confidence intervals is presented in Figures 6 and 7.

Table 3. Summary of results by subsamples of firms in industries with high/low intensity of intangible capital (total and macro-groups)

	Intangibles		Software & database		Innovation property		Economic competencies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Below p50	Over p50	Below p50	Over p50	Below p50	Over p50	Below p50	Over p50
BS (average bonus share)	-0.804***	-0.349	-1.159***	0.473	-0.644***	-0.108	-1.021***	0.199
	(0.169)	(0.242)	(0.120)	(0.429)	(0.183)	(0.173)	(0.140)	(0.406)
firm_fe (γ)	0.055***	0.055***	0.044***	0.072***	0.063***	0.056***	0.057***	0.063***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.011)	(0.006)	(0.006)
sh_female	-0.115***	-0.235***	-0.146***	-0.161***	-0.120***	-0.153*	-0.162***	-0.135***
	(0.020)	(0.032)	(0.021)	(0.028)	(0.021)	(0.080)	(0.022)	(0.029)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/country/region/ industries dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78,909	63,342	82,317	59,934	85,570	56,681	83,872	58,379

Notes: Standard errors, clustered at industry/country/year/region, are reported in parentheses. Controls include *d_fem_manager*, *av_tenure*, *public, firm_size, sh_high_occup*. All equations include region, industry, country, year and country*year effects. Overall results including all equations of the recursive system are reported in the Appendix (Tables A.4-A.7).
***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

The results of the split sample analysis clearly show that IP schemes attenuate the adjusted gender gap only in contexts less intangible capital intensive (Table 3, columns 1 and 2; Figure 6, top-left panel). The result is confirmed if, instead of the aggregate intangibles stock, we replicate the analysis in subsamples of high/low intensity of the three intangible capital components (Table 3, columns 3-8; Figure 6): (a) Software and databases; (b) Innovative property; (c) Economic competencies. It is worth noting that in all low-intangible intensity contexts the gap-reducing effect of IPS is remarkably stronger than that found in the general case (-0.56, see Table 2). A one percentage point (p.p.) increase in the firm-level average bonus reduces the gender pay gap by 1.16 p.p., 0.64 p.p. and 1.02 p.p. in contexts with low intensity of Software & databases, Innovative property and Economic competencies, respectively.

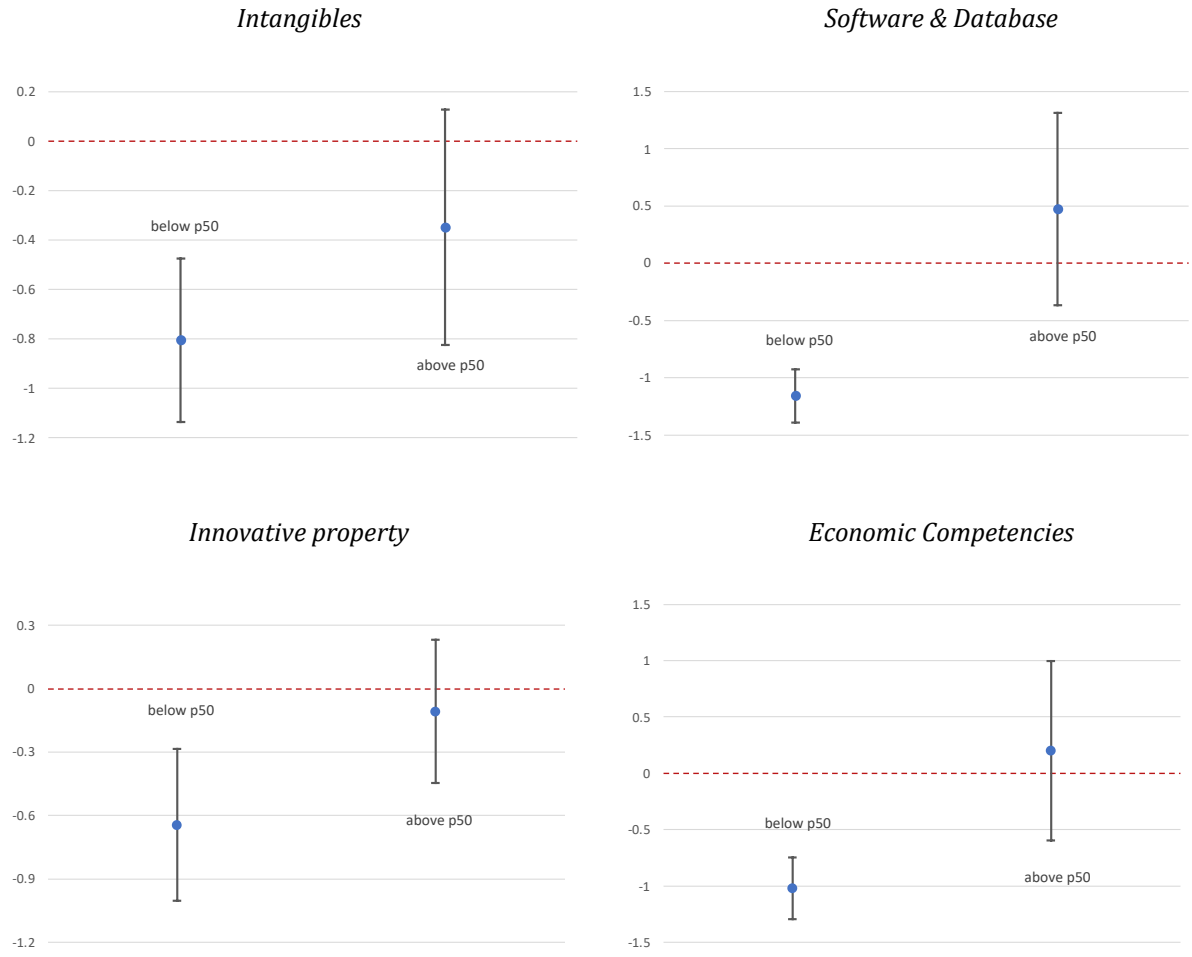
However, if we further break down the type of intangible capital where a finer detail is available (the components of Economic competencies), an interesting heterogeneity emerges. While, consistent with the results in Table 3 IP schemes do not play a role in contexts of high brand/ advertisement expenditures (Table 4, columns 1 and 2; Figure 7 top-right panel), they attenuate the adjusted wage gap in contexts of both low and high expenditures in organisational capital and training (Table 4, columns 3-6; Figure 7, bottom panels).

Table 4. Summary of results by subsamples of firms in industries with high/low intensity of intangible capital: components of 'economic competencies'

	Brand		Organisational capital		Training	
	(1)	(2)	(3)	(4)	(5)	(6)
	Below p50	Over p50	Below p50	Over p50	Below p50	Over p50
BS (average bonus share)	-0.935***	-0.010	-1.043***	-0.122***	-0.680***	-0.644**
	(0.154)	(0.324)	(0.112)	(0.047)	(0.159)	(0.286)
firm_fe (γ)	0.062***	0.055***	0.037***	0.089***	0.052***	0.065***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
sh_female	-0.155***	-0.136***	-0.141***	-0.093***	-0.148***	-0.145***
	(0.021)	(0.028)	(0.020)	(0.034)	(0.023)	(0.025)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/country/region/ industries dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	94,345	47,906	85,977	56,274	75,810	66,441

Notes: Standard errors, clustered at industry/country/year/ region, are reported in parentheses. Controls include *d_fem_manager*, *av_tenure*, *public, firm_size, sh_high_occup*. All equations include region, industry, country, year and country*year effects. Overall results including all equations of the recursive system are reported in the Appendix (Tables A.7-A.10).
***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

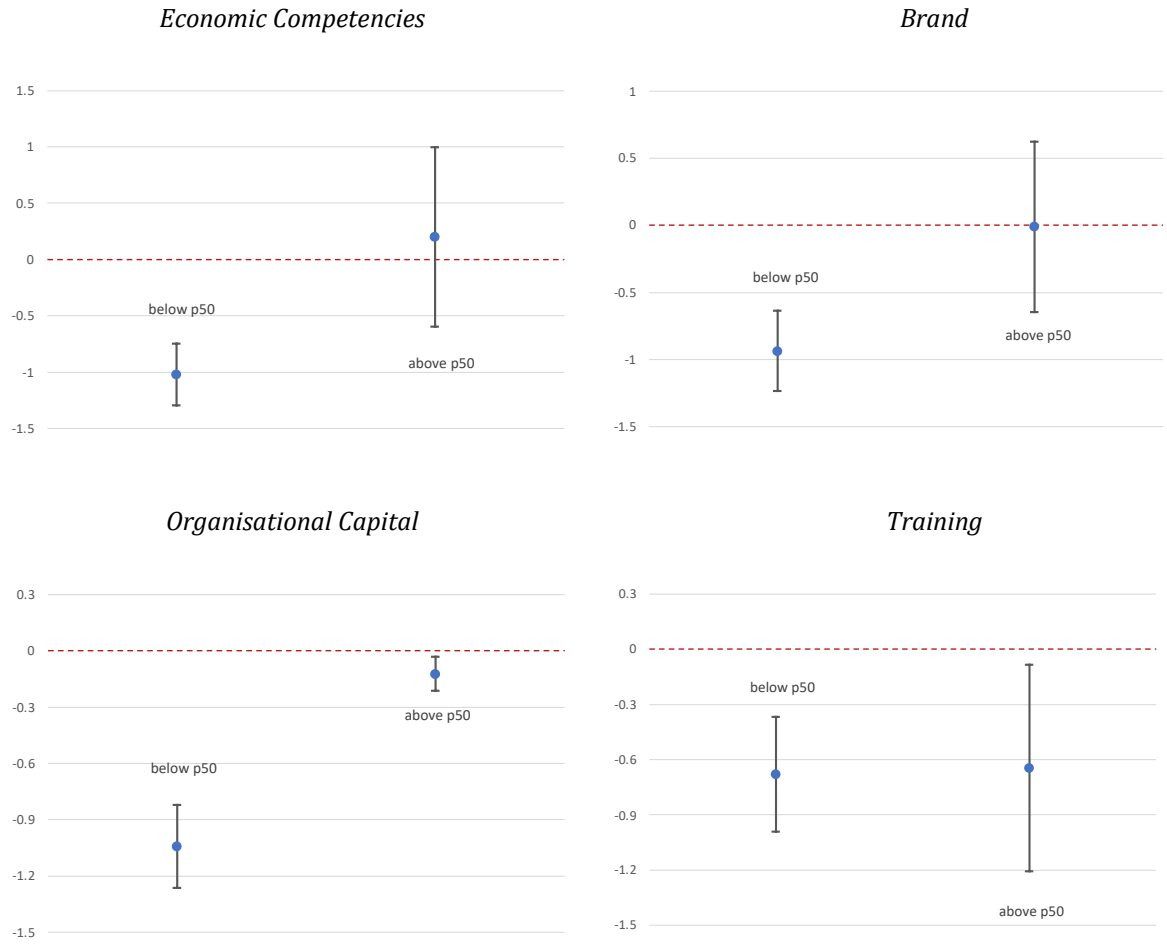
Figure 6. Effects of IPSs on the adjusted gender wage gap (coefficients and confidence intervals): aggregate intangibles and macro groups



Notes: The markers identify the coefficients of the BS variable presented in Table 3; the bars describe the 95% confidence intervals.

Overall, the evidence emerging from the split sample analysis corroborates our second research hypothesis. More intensive investments in database & software, scientific and non-scientific innovative activities, brand expenditures, market research and advertisement, push towards a flexibilisation of work models (longer and more unpredictable working hours/work schedules). In the presence of unequal sharing of household responsibilities, the potential of IPSs to attenuate gender disparities is dampened, as female workers are less likely to reach the targets set by the incentive schemes and get the bonus. The awareness, on both sides of the table, of such difficulties also probably decreases women's bargaining strength, by reducing the compensation claims and by increasing statistical discrimination practices from the employers' side (De La Rica *et al.*, 2015).

Figure 7. Effects of IPSs on the adjusted gender wage gap (coefficients and confidence intervals): economic competencies and its components



Notes: The markers identify the coefficients of the BS variable presented in Table 3 (Economic competencies) and Table 4 (the remaining diagrams); the bars describe the 95% confidence intervals.

By contrast, industries with highly developed organisational/business models probably make use of advanced monitoring systems and incentive schemes enabling a more effective implementation of IPSs, and this may reduce the needs for statistical discrimination. Likewise, where the development of workforce skills plays a crucial role, the recruitment of human resources is more effective (screening, probation mechanisms, etc.), so to maximise the returns to investments in training. This increases the probability that female workers hired in the company possess a working potential as high as their male counterparts, that can materialise in similar returns.

5.3. Robustness check

As discussed in Section 4, the equation system we used so far is based on a maximum likelihood method and might estimate inconsistent and biased parameters in presence of severe

heteroskedasticity (Roodman, 2011). To provide a robustness check for our results we use the control function approach, where the three equations have been estimated over two stages by means of OLS. In the first stage the endogenous variables, i.e., *average bonus share* and *sh_female*, have been regressed on excluded and included instruments (equations 3.2 and 3.3) and residuals from these estimations have been included in the second stage (equation 3.1) in order to take into account their potential endogeneity (Wooldridge, 2010; 2015). Table 5 reports results only for our main equation in the second stage, as outcomes for the first stage are virtually similar to those already reported in Tables A4-A10[13].

Overall, we can observe that differences between the coefficients estimated with the two approaches are not substantial. In the baseline estimation (Table 5, column 1), the impact of average bonus share on adjusted gender wage gap is -0.428 (compared to -0.564 in the system of equations, see Table 2, column 1) and that of the share of female is -0.157 (compared to -0.159, see Table 2, column 1). Also, in the split sample analysis (Table 5, columns 2-15) results obtained with the simultaneous equations system are substantially confirmed for each category of intangible capital and the difference between the estimated coefficients is minimal. The only exception is the result for high intensity organisational capital contexts (Table 5, column 11), where IPS is again negative but does not longer maintain its statistical significance in reducing the gender pay gap. Interestingly, the coefficients for the residuals (*av_bonus_sh_Res* and *s_fem_Res*) are almost always statistically significant, signaling that it is needed to treat both average bonus share and share of female variables as potentially endogenous.

[13] First stage results for the control function estimation are available upon request.

Table 5. Control function estimations: the effects of IP schemes on the adjusted gender wage gap (baseline and subsamples of firms in industries with high/low intensity of intangible capital)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Baseline	*Intangibles*		*Soft_DB*		*Innovprop*		*Econcomp*		*OrganCap*		*Training*		*Brand*	
		Below p50	Over p50	Below p50	Over p50	Below p50	Over p50	Below p50	Over p50	Below p50	Over p50	Below p50	Over p50	Below p50	Over p50
BS (average bonus share)	-0.428***	-0.697***	-0.193	-0.961***	0.269	-0.488***	-0.064	-0.754***	0.008	-1.017***	-0.013	-0.565***	-0.469**	-0.724***	0.016
	(0.136)	(0.167)	(0.231)	(0.135)	(0.293)	(0.173)	(0.084)	(0.146)	(0.344)	(0.104)	(0.095)	(0.154)	(0.222)	(0.154)	(0.309)
firm_fe (γ)	0.060***	0.055***	0.055***	0.043***	0.072***	0.063***	0.051***	0.056***	0.064***	0.037***	0.088***	0.052***	0.064***	0.060***	0.056***
	(0.004)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
sh_female	-0.157***	-0.114***	-0.232***	-0.144***	-0.160***	-0.119***	-0.189***	-0.159***	-0.135***	-0.139***	-0.110***	-0.145***	-0.143***	-0.154***	-0.134***
	(0.020)	(0.018)	(0.031)	(0.024)	(0.029)	(0.022)	(0.026)	(0.022)	(0.026)	(0.020)	(0.033)	(0.020)	(0.023)	(0.022)	(0.029)
av_bonus_sh_Res	0.392***	0.660***	0.302***	0.921***	-0.287	0.442***	0.056	0.757***	-0.07	0.979***	-0.002	0.537***	0.433*	0.699***	-0.059
	(0.133)	(0.161)	(0.033)	(0.132)	(0.290)	(0.173)	(0.085)	(0.145)	(0.335)	(0.102)	(0.092)	(0.151)	(0.222)	(0.152)	(0.305)
sh_female_Res	0.212***	0.157***	0.167	0.201***	0.216***	0.163***	0.268***	0.208***	0.203***	0.199***	0.168***	0.198***	0.064***	0.203***	0.209***
	(0.020)	(0.019)	(0.227)	(0.025)	(0.030)	(0.023)	(0.026)	(0.022)	(0.027)	(0.019)	(0.034)	(0.021)	(0.005)	(0.023)	(0.029)
d_fem_manager	0.006***	0.010***	0.004	0.007***	0.002	0.006**	0.004	0.012***	0.000	0.006***	0.000	0.008***	0.005	0.007***	0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)
av_tenure	0.001**	0.002***	0.000	0.002***	-0.001**	0.001**	-0.000*	0.002***	-0.001	0.002***	-0.000*	0.002***	0.000	0.002***	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
public	-0.010***	-0.004	-0.018***	-0.006**	-0.019***	-0.004	-0.016***	-0.009***	-0.015***	-0.009***	-0.017***	-0.007**	-0.019***	-0.011***	-0.021***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
fsize (medium)	0.002	0.008***	-0.005	0.010***	-0.006	0.002	0.000	0.006**	-0.004	0.011***	-0.004	0.006**	0.002	0.005**	-0.004
	(0.002)	(0.003)	(0.004)	(0.002)	(0.005)	(0.003)	(0.003)	(0.003)	(0.006)	(0.002)	(0.005)	(0.002)	(0.004)	(0.002)	(0.006)
fsize (large)	-0.004	0.011***	-0.027***	0.015***	-0.031***	0.002	-0.020***	0.007*	-0.027**	0.018***	0.016*	0.009**	-0.014*	0.008**	-0.027***
	(0.004)	(0.004)	(0.007)	(0.004)	(0.008)	(0.005)	(0.003)	(0.004)	(0.011)	(0.003)	(0.008)	(0.003)	(0.007)	(0.004)	(0.010)
s_high_occup	0.019***	0.029***	0.010	0.030***	0.006	0.030***	0.000	0.023***	0.014	0.028***	0.018***	0.019**	0.025***	0.030***	0.004
	(0.005)	(0.008)	(0.007)	(0.007)	(0.010)	(0.007)	(0.005)	(0.007)	(0.011)	(0.006)	(0.005)	(0.007)	(0.007)	(0.007)	(0.010)
Y/c/r/i/FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	142,095	78,850	63,245	82,267	59,828	85,513	56,582	83,835	58,260	85,833	56,262	75,729	66,366	94,287	47,808
R-squared	0.047	0.048	0.049	0.061	0.044	0.051	0.047	0.053	0.041	0.062	0.044	0.056	0.038	0.048	0.046

Notes: Standard errors, clustered at industry/country/year/ region, are reported in parentheses. Bootstrapping procedure has been applied to correctly estimate standard errors in the second stage. All equations include region, industry, country, year and country*year effects (*Y/c/r/i/FE)*. According to the control function approach (Wooldridge, 2010; 2015), av_bonus_sh_Res and s_female_Res are residuals from the first stage where the two endogenous variables are regressed on the same instruments used for the simultaneous equation systems. We omitted the first stage of control function estimation because results are very similar to those reported for simultaneous equation systems, however these first stage results are available upon request. Statistical significance for the residual coefficients indicates endogeneity of the key variables av_bonus_share and s_female.
***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

6. Conclusions

Incentive pay schemes (IPSs) have been attracting increasing interest in recent years among scholars and policy makers, as managerial practices capable to realign wages to productivity and, therefore, positively contribute to firm performances and economic growth. At the same time, concerns raised by researchers on gender issues have highlighted that the diffusion of variable pay systems may fuel a further widening of gender wage gap between and within firms, due to segregation of women into workplaces without incentive pay or due to their less bargaining power and propensity to negotiate compared to men.

Our study offers a contribution to the debate from the perspective of companies and workers residing in the four major EU economies (France, Germany, Italy and Spain) plus the United Kingdom, in years 2006, 2010, 2014 and 2018. To this aim, we analysed the effect of IPSs on adjusted gender wage gap by relying on methods able to account for potential endogeneity issues. Namely, we rely on the estimation of a system of simultaneous equations and on a control function approach as robustness check. Despite providing a contribution in terms of methods applied and empirical evidence, our analysis has some important limitations related to the data set used. First, our results should be confirmed using data with longitudinal structure, to control for unobserved heterogeneity of firms more accurately. In addition, we are aware that proper controls for self-selection of women should be applied by using panel data models and workers flows between firms. Furthermore, SES data, despite providing information on collective bargaining, do not allow us applying a finer grained distinction between individual and collective bonuses, that could be crucial to disentangle the effects of IPSs on the adjusted gender pay gap. These limitations are offset by the accuracy of harmonised data for a large number of countries and years.

Our empirical investigation is developed around two research hypotheses. In the first one (H1), we hypothesised and find empirical evidence that when using an adjusted metric of within-firm gender wage gap (i.e., the component of this gap not explained by individual and productive characteristics of workers) and controlling for segregation of women into low wage jobs and firms, IPSs help reducing the gender pay. This might be due to the fact that firms implementing performance pay schemes are able to attract not only male, but also female workers with desirable unobserved characteristics and preferences (e.g., high productivity and high risk-propensity women, and those less constrained by household workloads), as they are aware that they can reach the targets and the bonus remuneration and gain a higher remuneration. In addition, being IPSs also designed to address asymmetric information issues, firms more intensively

adopting such schemes might be less inclined to resort statistical discrimination against women, due to the presence of better screening and monitoring devices.

In the second research question (H2), we conjectured that the reasons behind the attenuating effect of IPSs on the adjusted gender pay gap could be differently moderated by the intensity with which the various types intangible assets spread across industries. We find that splitting the sample between industries with different categories of low- and high-intensive intangible assets (software/database, innovative property, brand and advertisement expenditures), the gap-reducing effect of IPSs only holds for contexts with low levels (below the median) of such intangible capital stock. Our explanation for this evidence relies on the relevant changes produced by these intangibles on the business models and labour organisation of companies, as they push towards increasing flexibilisation and unpredictability of working time that make the gender equalising mechanisms related to IPSs ineffective. In the presence of asymmetries in household workloads, female workers are less likely to reach the target, hence falling behind their male counterparts with reference to the variable part of their remuneration. In addition, the awareness of this disadvantage will render IPSs intensive contexts less attractive for high-potential female workers or decrease their bargaining strength, while increasing the probability of statistical discrimination practices from the side of the employers.

Interestingly, an exception to these general results, also confirmed by robustness checks, is the case of training expenditures, for which we find that the effectiveness of IPSs in reducing the gender pay gap is not weakened by higher levels of investments in firm-specific human capital. In this case, the recourse to statistical discrimination by the employers is probably less frequent, as the recruitment of human resources is more effective (screening, probation mechanisms, etc.), so to maximise the returns to investments in training. This is likely to increase the probability that female workers hired in the company possess a working potential as high as their male counterparts, that can materialise in similar returns.

An important policy implication of our study is that it is not the IPSs *'per se'* that exacerbates gender pay inequality, but the specific technological context in which its implementation takes place. This calls for policy arrangements aimed at changing the allocation across genders of unpaid work, as suggested by the Work-Life Balance Directive (European Commission, 2022). However, our results also suggest that providing incentives to increase training is another channel to contrast the potential negative effects of the disruptive technologies on the gender pay gap.

References

Aghelmaleki, H., Bachmann, R. & Stiebale. J. (2021). 'The China shock, employment protection, and European jobs', *ILR Review*, November.

Aghion, P., Akcigit, U., Hyytinen, A., & Toivanen, O. (2018). 'On the returns to invention within firms: Evidence from Finland', *AEA Papers and Proceedings*, 108, 208-212.

Arabadjieva, K., & Zwysen, W. (2022). 'Gender inequality in performance-related pay: a gap in the EU equal pay agenda', *ETUI Research Paper-Policy Brief*., ETUI, Brussels.

Asplund, R. & Napari, S. (2011). 'Intangibles and the gender wage gap: An analysis of gender wage gaps across occupations in the Finnish private sector', *ETLA Discussion Papers*, 1243, The Research Institute of the Finnish Economy (ETLA), Helsinki.

Barth, E., T. Gulbrandsen & Schønea, P. (2005). 'Family ownership and productivity: the role of owner-management', *Journal of Corporate Finance*, 11(1–2), 107–127.

Biasi, B., & Sarsons, H. (2022). 'Flexible wages, bargaining, and the gender gap', *The Quarterly Journal of Economics*, 137(1), 215-266.

Blau, F. D., & Kahn, L.M. (2017). 'The gender wage gap: Extent, trends, and explanations', *Journal of Economic Literature*, 55(3), 789-865.

Bloom, N., & Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. The quarterly journal of Economics, 122(4), 1351-1408.

Bloom, N., & Van Reenen, J. (2011).' Human resource management and productivity', in *Handbook of labor economics*, 4, 1697-1767, Elsevier.

Bryson, A., Freeman, R., Lucifora, C., Pellizzari, M., & Perotin, V. (2012). 'Paying for performance: incentive pay schemes and employees' financial participation', *CEP discussion paper*, *1112*, 52-75.

Caliendo, M., Fedorets, A., Preuss, M., Schröder, C., & Wittbrodt, L. (2018). 'The short-run employment effects of the German minimum wage reform', *Labour Economics*, 53, 46-62.

Card, D., Cardoso, A.R., & Kline, P. 2016. 'Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women', *The Quarterly Journal of Economics,* 131(2), 633-686.

Card, D., Cardoso, A. R., Heining, J., & Kline, P. (2018). 'Firms and labor market inequality: Evidence and some theory', *Journal of Labor Economics*, 36(S1), S13-S70.

Cirillo, V., Sostero, M., & Tamagni, F. (2017). 'Innovation and within-firm wage inequalities: empirical evidence from major European countries', *Industry and Innovation*, 24(5), 468-491.

Corrado, C., Hulten, C., & Sichel, D. (2005). 'Measuring capital and technology: an expanded framework', in C. Corrado, J. Haltiwanger, & D. Sichel (eds), *Measuring capital in the new economy* ,65, 11-46, University of Chicago Press.

Corrado, C., Hulten, C., & Sichel, D. (2009). 'Intangible capital and US economic growth', *Review of Income and Wealth*, 55(3), 661-685.

Cruz, C., Firfiray, S., & Gomez-Mejia, L. R. (2011). 'Socioemotional wealth and human resource management (HRM) in family-controlled firms', in A. Joshi, H. Liao, & J. J. Martocchio (Eds.), *Research in personnel and human resources management*, 30, 159–217, Bingley: Emerald Group Publishing Limited.

De La Rica, S., Dolado, J. J., & Vegas, R. (2015). 'Gender gaps in performance pay: new evidence from Spain', *Annals of Economics and Statistics/Annales d'Economie et de Statistique*, 117/118, 41-59.

Derks, B., Van Laar, C. & Ellemers, N. (2016). 'The queen bee phenomenon: why women leaders distance themselves from junior women', *Leadership Quarterly*, 27, 456–469.

Eurofound. (2021). 'Understanding the gender pay gap: What role do sector and occupation play?', *European Jobs Monitor series*, Publications Office of the European Union, Luxembourg.

European Commission. (2022). '(2022) report of gender equality in the EU', *Commission Staff Working Document*, Bruxelles.

Gittleman, M., & Pierce, B. (2015). 'Pay for performance and compensation inequality: Evidence from the ECEC', *ILR Review*, 68(1), 28-52.

Goldin, C. 2014. 'A grand gender convergence: Its last chapter', *American Economic Review*, 104/4, 1091-1119.

ILO. (2016). Global wage report 2016/17: Wage inequality in the workplace, Geneva, ILO.

Kato, T., & Kodama, N. (2018). 'Women in the workplace and management practices', in Averett, S., & Hoffman, S. D. (Eds.) *The Oxford handbook of women and the economy*, Oxford University Press.

Korkeamäki, O., & Kyyrä, T. (2006). 'A gender wage gap decomposition for matched employer–employee data', *Labour Economics*, 13(5), 611-638.

Lazear, E. (2000). 'Performance pay and productivity', *American Economic Review*, 90(5), 1346-1361.

Lazear, E. P. (1986). 'Salaries and piece rates', *The Journal of Business*, 59, 405–431.

Lazear, E. P., & Rosen, S. (1981).' Rank-order tournaments as optimum labor contracts'. *Journal of Political Economy*, 89, 841–864.

Lewandowski, P., Madoń, K., Bachmann, R. & Gonschor, M. (2022). 'The impact of robots on labour market transitions in Europe', *IBS Working Papers*, 01/(2022), Instytut Badan Strukturalnych.

Leythienne D., & Pérez-Juliàn M., (2021). *Gender pay gaps in the European Union: A statistical analysis*, Luxembourg: Publications Office of the European Union.

Manning, A., & Saidi, F. (2010). 'Understanding the gender pay gap: what's competition got to do with it?', *ILR Review*, 63(4), 681-698.

Marsden, D., & Belfield, R. (2010). 'Institutions and the management of human resources: Incentive pay systems in France and Great Britain', *British Journal of Industrial Relations*, 48(2), 235-283.

Meyersson Milgrom, E. M., Petersen, T., & Snartland, V. (2001). 'Equal pay for equal work? Evidence from Sweden and a comparison with Norway and the US', *Scandinavian Journal of Economics*, 103(4), 559-583.

Moreno-Galbis, E., & Wolff, F. C. (2008). 'New technologies and the gender wage gap: Evidence from France', *Relations Industrielles/Industrial Relations*, 63(2), 317-339.

Murphy, K. J. (1999). 'Executive compensation', *Handbook of Labor Economics*, 3, 2485–2563.

OECD. (2017). Dare to Share: Germany's Experience Promoting Equal Partnership in Families, OECD Publishing, Paris.

OECD. (2019). Part-time and Partly Equal: Gender and Work in the Netherlands, OECD Publishing, Paris.

OECD. (2021). The Role of Firms in Wage Inequality: Policy Lessons from a Large Scale Cross-Country Study, OECD Publishing, Paris.

Ponzellini, A. M., Aumayr, C., & Wolf, F. (2010). Addressing the gender pay gap: Government and social partner actions, Eurofound Report.

Roodman, D. (2011). 'Fitting fully observed recursive mixed-process models with cmp', *The Stata Journal*, 11(02), 159–206

Rusinek, M., & Rycx, F. (2013). 'Rent-sharing under different bargaining regimes: Evidence from linked employer–employee data', *British Journal of Industrial Relations*, *51*(1), 28-58.

Segovia-Pérez, M., Castro Núñez, R. B., Santero Sánchez, R., & Laguna Sánchez, P. (2020). 'Being a woman in an ICT job: An analysis of the gender pay gap and discrimination in Spain', *New Technology, Work and Employment*, 35 (1), 20-39.

Van Hek, M., & Van Der Lippe, T. (2019). 'Are female managers agents of change or cogs in the machine? an assessment with three-level manager–employee linked data', *European Sociological Review*, 35(3), 316-331.

Winter-Ebmer, R., & Zweimüller, J. (1999). 'Intra-firm wage dispersion and firm performance', *Kyklos*, *52*(4), 555-572.

Wooldridge, J. M. (2015). 'Control function methods in applied econometrics', *Journal of Human Resources*, 50(2), 420-445.

Zellner, A. (1962). 'An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias', *Journal of the American statistical Association*, *57*(298), 348-368.

Zwysen, W. (2021). 'Performance pay across Europe: drivers of the increase and the link with wage inequality', *ETUI Research Paper* - Working Paper 2021.06, ETUI, Brussels.

Zwysen, W. (2022). 'Wage inequality within and between firms: Macroeconomic and institutional drivers in Europe', *ETUI Research Paper* - Working Paper, 2022.02, ETUI, Brussels.

Appendix

Table A1 Variables definition

Acronym	Definition
Firm level variables (Source: Structure of Earnings Survey – SES)	
Raw Gender Gap	Difference between logs of male and female hourly wage
BS (average bonus share)	Average of the share of bonuses/allowances over the total remunerations (%)
sh_female	Share of female employees (%)
sh_tert	Share of workers with tertiary education (%)
sh_part	Share of part-time workers (%)
sh_temp	Share of temporary workers (%)
inn_firm	Presence of at least one employee in the occupation 21 of ISCO-08 classification 'Science and engineering professionals' (dummy variable)
nocollbarg	Firm without any form of collective agreement in wage-setting (dummy variable)
sh_manager	Share of workers employed as managers (group 1 of the ISCO-08 classification) (%)
sh_fem_manager	Share of female managers on total managers (%)
d_fem_manager	Presence of female managers (dummy variable)
av_tenure	Average of the length of service in enterprise (years)
public	Firm under public control (dummy variable)
fsize (small)	Establishment with less than 50 employees (dummy variable)
fsize (medium)	Establishment with 50-249 employees (dummy variable)
fsize (large)	Establishment with over 250 employees (dummy variable)
sh_high_occup	Share of workers employed in high-rank occupation (group 1-3 of the ISCO-08 classification) (%)
Industry level variables, Intangible capital (Source: EU-KLEMS & INTANProd)	
Intangibles	Total Intangible Capital stock per worker (real net capital stock per worker, ppp 2018)
Database & Software	Value of Software & Database (real net capital stock per worker, ppp 2018)
Innovative Property	Value of Innovative property (real net capital stock per worker, ppp 2018)
Economic Competencies	Value of Economic Competencies (real net capital stock per worker, ppp 2018)
Brand	Expenditures on advertising and market research (real net capital stock per worker, ppp 2018)
Organisational capital	Executive time spent on improving the effectiveness of business organisations, on developing business models and corporate cultures (real net capital stock per worker, ppp 2018)
Training	Expenditures on employer-provided training (real net capital stock per worker, ppp 2018)

Source: Own elaborations from SES and EU-KLEMS data.

Table A2 Share of workers in the sample by type of contract and education (average 2006-2010-2014-2018)

	Temporary	Part-time	Primary Ed.	Secondary Ed.	Tertiary Ed.
Totale Sample					
Total	0.116	0.246	0.185	0.571	0.244
Female	0.131	0.388	0.193	0.575	0.233
Male	0.104	0.131	0.179	0.568	0.253
Germany					
Total	0.116	0.300	0.153	0.684	0.163
Female	0.131	0.487	0.173	0.696	0.131
Male	0.104	0.158	0.138	0.674	0.188
Italy					
Total	0.075	0.142	0.283	0.463	0.254
Female	0.082	0.246	0.246	0.474	0.280
Male	0.070	0.056	0.314	0.454	0.232
Spain					
Total	0.214	0.161	0.353	0.257	0.390
Female	0.234	0.219	0.338	0.259	0.403
Male	0.194	0.105	0.368	0.255	0.377
France					
Total	0.066	0.132	0.115	0.378	0.507
Female	0.078	0.201	0.114	0.403	0.482
Male	0.054	0.070	0.115	0.355	0.530
United Kingdom					
Total	0.092	0.276	0.107	0.507	0.386
Female	0.094	0.377	0.107	0.504	0.388
Male	0.090	0.146	0.107	0.511	0.382

Source: own elaborations from SES data

Table A3 Industries with low and high intensity of intangible capital

Industries	Total intangibles		Software& database		Innovative property		Economic competencies	
	Below p50	*Over p50*	*Below p50*	*Over p50*	*Below p50*	*Over p50*	*Below p50*	*Over p50*
Mining and quarrying		X		X		X	X	
Food products, beverages and tobacco		X	n.c.	n.c.	X			X
Textiles, wearing apparel, leather and related prodcuts	X		X		X			X
Wood and paper products; printing and reproduction of recorded media	X			X	X			X
Ref. petroleum, chemicals and pharma		X		X		X		X
Rubber, plastic and Non metallic mineral products		X	X			X		X
Basic metals and metal products	X		X			X	n.c.	n.c.
Electrical equipment, computer and repair		X		X		X	n.c.	n.c.
Machinery		X		X		X		X
Motorvehicles and other transport equipment		X		X		X	X	
Furniture and other manuf.		X		X		X		X
Utilities		X		X		X		X
Construction	X		X		X		X	
Wholesale	X		X		X			X
Retail trade	X		X		X		X	
Transportation	X			X	X		X	
Accomodation and food services	X		X		X		X	
Publishing and broacasting activities		X		X		X		X
Telecommunications, comp. programm. and informations		X		X		X		X
Finance		X		X	X			X
Real estate, R&D, advert. and other professional activities		X		X		X	X	
Administrative and support services	X		X		X		X	
Education		X	X		n.c.	n.c.	X	
Health	X		X		X		X	
Community, social and personal services	X			X	X		X	

Industries	Economic Competencies		Organisational Capital		Brand Expenditures		Training	
	Below p50	*Over p50*	*Below p50*	*Over p50*	*Below p50*	*Over p50*	*Below p50*	*Over p50*
Mining and quarrying	X			X	X			X
Food products, beverages and tobacco		X	X			X	X	
Textiles, wearing apparel, leather and related prodcuts		X	X			X	X	
Wood and paper products; printing and reproduction of recorded media		X	X			X	X	
Ref. petroleum, chemicals and pharma		X		X		X		X
Rubber, plastic and Non metallic mineral products		X	X		X		X	
Basic metals and metal products	n.c.	n.c.	X		X		X	
Electrical equipment, computer and repair	n.c.	n.c.	n.c.	n.c.		X		X
Machinery		X		X				X
Motorvehicles and other transport equipment	X			X		X		X
Furniture and other manuf.		X	X			X	n.c.	n.c.
Utilities		X		X	X			X
Construction	X		X		X			X
Wholesale		X		X		X		X
Retail trade	X		X		X		X	
Transportation	X		X		X		X	
Accomodation and food services	X		X		X		X	
Publishing and broacasting activities		X		X		X	X	
Telecommunications, comp. programm. and informations		X		X		X		X
Finance		X		X		X		X
Real estate, R&D, advert. and other professional activities	X			X		X		X
Administrative and support services	X		X		X		X	
Education	X		X		X		X	
Health	X		X		X		X	
Community, social and personal services	X		X		X		X	

Source: Own elaborations from EU-KLEMS data. Notes: the attribution of each industry to the Below/Over p50 group follows a majority criterion whenever the twenty observations (5 countries x 4 years) are unevenly allocated between Below and Over p50. When the observations are equally distributed between the two groups, they are identified as 'not classified' (n.c.).

Table A4 Split sample analysis: effects of IPS on the adjusted gender wage gap in sectors with low and high intensity of intangible capital (total)

	Below p50			Over p50		
	Adj. gender gap	sh_female	BS	Adj. gender gap	sh_female	BS
BS (average bonus share)	-0.804***	-0.723***		-0.349	-1.477***	
	(0.169)	(0.266)		(0.242)	(0.257)	
firm_fe (γ)	0.055***	0.000		0.055***	-0.066***	
	(0.006)	(0.010)		(0.006)	(0.007)	
sh_female	-0.115***			-0.235***		
	(0.020)			(0.032)		
sh_tert		0.013			0.009	
		(0.008)			(0.006)	
sh_part		0.242***			0.210***	
		(0.011)			(0.011)	
sh_temp		0.010*			0.025***	
		(0.005)			(0.009)	
inn_firm			0.009***			0.008***
			(0.001)			(0.001)
nocollbarg			-0.013***			-0.012***
			(0.001)			(0.002)
sh_manager			0.034***			0.038***
			(0.005)			(0.005)
d_fem_manager	0.011***	0.053***	0.003***	0.006*	0.057***	0.004***
	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)
av_tenure	0.002***	0.003***	0.002***	0.000	0.003***	0.002***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
public	-0.005	0.018***	-0.006***	-0.019***	0.019***	-0.008***
	(0.003)	(0.005)	(0.001)	(0.003)	(0.005)	(0.002)
fsize (medium)	0.009***	0.008*	0.009***	-0.002	0.012**	0.013***
	(0.003)	(0.004)	(0.001)	(0.004)	(0.005)	(0.001)
fsize (large)	0.013***	0.016***	0.015***	-0.023***	0.012	0.026***
	(0.004)	(0.006)	(0.001)	(0.007)	(0.009)	(0.001)
sh_high_occup	0.033***	0.036***	0.029***	0.014*	0.021**	0.021***
	(0.008)	(0.013)	(0.002)	(0.007)	(0.010)	(0.002)
Constant	0.150***	0.279***	0.081***	0.122***	0.397***	0.065***
	(0.034)	(0.039)	(0.016)	(0.029)	(0.023)	(0.005)
Year/country/region/ industries dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78,909	78,909	78,909	63,342	63,342	63,342

Notes: Standard errors, clustered at industry/country/year/region, are reported in parentheses. All equations include region, industry, country, year and country*year effects.
***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table A5 Split sample analysis: effects of IPS on the adjusted gender wage gap in sectors with low and high intensity of intangible capital (database & software)

	Below p50			Over p50		
	Adj. gender gap	sh_female	BS	Adj. gender gap	sh_female	BS
BS (average bonus share)	-1.159***	-1.498***		0.473	-0.397	
	(0.120)	(0.225)		(0.429)	(0.350)	
firm_fe (γ)	0.044***	-0.011		0.072***	-0.072***	
	(0.006)	(0.010)		(0.006)	(0.008)	
sh_female	-0.146***			-0.161***		
	(0.021)			(0.028)		
sh_tert		-0.019**			0.031***	
		(0.008)			(0.006)	
sh_part		0.239***			0.220***	
		(0.012)			(0.010)	
sh_temp		0.012**			0.010	
		(0.005)			(0.009)	
inn_firm			0.010***			0.003
			(0.001)			(0.002)
nocollbarg			-0.013***			-0.012***
			(0.001)			(0.004)
sh_manager			0.047***			0.040***
			(0.005)			(0.005)
d_fem_manager	0.008***	0.056***	0.002**	-0.000	0.049***	0.005***
	(0.002)	(0.003)	(0.001)	(0.005)	(0.004)	(0.001)
av_tenure	0.003***	0.004***	0.002***	-0.002*	0.000	0.002***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
public	-0.008**	0.022***	-0.008***	-0.018***	0.017***	-0.005**
	(0.004)	(0.005)	(0.001)	(0.004)	(0.004)	(0.002)
fsize (medium)	0.012***	0.014***	0.010***	-0.009	0.001	0.014***
	(0.002)	(0.004)	(0.001)	(0.007)	(0.006)	(0.001)
fsize (large)	0.019***	0.029***	0.017***	-0.037***	-0.014	0.025***
	(0.003)	(0.006)	(0.001)	(0.011)	(0.010)	(0.002)
sh_high_occup	0.036***	0.080***	0.027***	0.001	-0.019*	0.022***
	(0.006)	(0.012)	(0.002)	(0.012)	(0.011)	(0.002)
Constant	0.145***	0.324***	0.062***	0.042	0.327***	0.068***
	(0.019)	(0.026)	(0.007)	(0.046)	(0.029)	(0.007)
Year/country/region/ industries dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82,317	82,317	82,317	59,934	59,934	59,934

Notes: Standard errors, clustered at industry/country/year/ region, are reported in parentheses. All equations include region, industry, country, year and country*year effects.
***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table A6 Split sample analysis: effects of IPS on the adjusted gender wage gap in sectors with low and high intensity of intangible capital (innovative property)

	Below p50			Over p50		
	Adj. gender gap	sh_female	BS	Adj. gender gap	sh_female	BS
BS (average bonus share)	-0.644***	-1.041***		-0.108	-0.782	
	(0.183)	(0.262)		(0.173)	(0.483)	
firm_fe (γ)	0.063***	0.003		0.056***	-0.070***	
	(0.006)	(0.009)		(0.011)	(0.019)	
sh_female	-0.120***			-0.153*		
	(0.021)			(0.080)		
sh_tert		0.013*			0.005	
		(0.007)			(0.019)	
sh_part		0.238***			0.208***	
		(0.011)			(0.028)	
sh_temp		0.010*			0.026	
		(0.005)			(0.017)	
inn_firm			0.011***			0.006**
			(0.001)			(0.003)
nocollbarg			-0.012***			-0.014***
			(0.001)			(0.002)
sh_manager			0.039***			0.030***
			(0.005)			(0.011)
d_fem_manager	0.008***	0.054***	0.004***	0.002	0.055***	0.003**
	(0.003)	(0.003)	(0.001)	(0.004)	(0.005)	(0.002)
av_tenure	0.001***	0.003***	0.002***	-0.000	0.001	0.002***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
public	-0.005	0.018***	-0.005***	-0.018***	0.024***	-0.009**
	(0.003)	(0.005)	(0.001)	(0.005)	(0.008)	(0.004)
fsize (medium)	0.004	0.015***	0.010***	0.001	-0.004	0.012***
	(0.003)	(0.004)	(0.001)	(0.003)	(0.008)	(0.001)
fsize (large)	0.006	0.025***	0.017***	-0.017***	-0.018	0.023***
	(0.004)	(0.006)	(0.001)	(0.005)	(0.016)	(0.002)
sh_high_occup	0.035***	0.028**	0.026***	0.001	0.024	0.023***
	(0.008)	(0.011)	(0.002)	(0.011)	(0.023)	(0.004)
Constant	0.146***	0.452***	0.046***	0.071**	0.365***	0.065***
	(0.016)	(0.016)	(0.005)	(0.034)	(0.034)	(0.005)
Year/country/region/ industries dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85,570	85,570	85,570	56,681	56,681	56,681

Notes: Standard errors, clustered at industry/country/year/ region, are reported in parentheses. All equations include region, industry, country, year and country*year effects.
***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table A7 Split sample analysis: effects of IPS on the adjusted gender wage gap in sectors with low and high intensity of intangible capital (economic competencies)

	Below p50			Over p50		
	Adj. gender gap	sh_female	BS	Adj. gender gap	sh_female	BS
BS (average bonus share)	-1.021***	-1.446***		0.199	-0.582**	
	(0.140)	(0.246)		(0.406)	(0.268)	
firm_fe (γ)	0.057***	-0.012		0.063***	-0.068***	
	(0.006)	(0.009)		(0.006)	(0.009)	
sh_female	-0.162***			-0.135***		
	(0.022)			(0.029)		
sh_tert		-0.002			0.019***	
		(0.007)			(0.007)	
sh_part		0.229***			0.226***	
		(0.011)			(0.012)	
sh_temp		0.012**			0.013	
		(0.005)			(0.010)	
inn_firm			0.011***			0.005***
			(0.001)			(0.002)
nocollbarg			-0.013***			-0.011***
			(0.001)			(0.003)
sh_manager			0.055***			0.029***
			(0.006)			(0.005)
d_fem_manager	0.014***	0.056***	0.001**	-0.002	0.051***	0.004***
	(0.002)	(0.003)	(0.001)	(0.004)	(0.003)	(0.001)
av_tenure	0.002***	0.004***	0.002***	-0.001	0.001	0.002***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
public	-0.010***	0.022***	-0.004**	-0.013***	0.013**	-0.010***
	(0.003)	(0.005)	(0.001)	(0.005)	(0.005)	(0.002)
fsize (medium)	0.008***	0.011***	0.008***	-0.007	0.003	0.016***
	(0.003)	(0.004)	(0.001)	(0.008)	(0.006)	(0.001)
fsize (large)	0.011***	0.023***	0.014***	-0.033**	-0.010	0.029***
	(0.003)	(0.005)	(0.001)	(0.013)	(0.010)	(0.001)
sh_high_occup	0.031***	0.047***	0.022***	0.009	0.010	0.027***
	(0.006)	(0.011)	(0.002)	(0.013)	(0.011)	(0.002)
Constant	0.120***	0.343***	0.073***	0.073*	0.324***	0.062***
	(0.023)	(0.025)	(0.007)	(0.042)	(0.027)	(0.007)
Year/country/region/ industries dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83,872	83,872	83,872	58,379	58,379	58,379

Notes: Standard errors, clustered at industry/country/year/ region, are reported in parentheses. All equations include region, industry, country, year and country*year effects.
***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table A8 Split sample analysis: effects of IPS on the adjusted gender wage gap in sectors with low and high intensity of intangible capital (brand)

	Below p50			Over p50		
	Adj. gender gap	sh_female	BS	Adj. gender gap	sh_female	BS
BS (average bonus share)	-0.935***	-1.036***		-0.010	-1.140***	
	(0.154)	(0.235)		(0.324)	(0.249)	
firm_fe (γ)	0.062***	-0.011		0.055***	-0.083***	
	(0.006)	(0.008)		(0.007)	(0.009)	
sh_female	-0.155***			-0.136***		
	(0.021)			(0.028)		
sh_tert		-0.005			0.025***	
		(0.007)			(0.006)	
sh_part		0.225***			0.248***	
		(0.010)			(0.013)	
sh_temp		0.002			0.054***	
		(0.005)			(0.010)	
inn_firm			0.007***			0.010***
			(0.001)			(0.001)
nocollbarg			-0.014***			-0.011***
			(0.001)			(0.003)
sh_manager			0.038***			0.029***
			(0.005)			(0.005)
d_fem_manager	0.009***	0.056***	0.002***	0.002	0.053***	0.006***
	(0.002)	(0.003)	(0.001)	(0.004)	(0.004)	(0.001)
av_tenure	0.002***	0.003***	0.002***	-0.000	0.001*	0.002***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
public	-0.012***	0.016***	-0.005***	-0.021***	0.021***	-0.015***
	(0.003)	(0.004)	(0.001)	(0.005)	(0.007)	(0.004)
fsize (medium)	0.008***	0.007**	0.010***	-0.003	0.009	0.014***
	(0.002)	(0.004)	(0.001)	(0.006)	(0.006)	(0.001)
fsize (large)	0.013***	0.016***	0.017***	-0.027***	0.007	0.027***
	(0.004)	(0.005)	(0.001)	(0.010)	(0.009)	(0.002)
sh_high_occup	0.036***	0.057***	0.027***	0.005	-0.008	0.023***
	(0.007)	(0.011)	(0.002)	(0.010)	(0.010)	(0.002)
Constant	0.152***	0.288***	0.064***	0.074	0.391***	0.074***
	(0.021)	(0.025)	(0.008)	(0.048)	(0.028)	(0.008)
Year/country/region/ industries dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	94,345	94,345	94,345	47,906	47,906	47,906

Notes: Standard errors, clustered at industry/country/year/ region, are reported in parentheses. All equations include region, industry, country, year and country*year effects.
***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table A9 Split sample analysis: effects of IPS on the adjusted gender wage gap in sectors with low and high intensity of intangible capital (organisational capital)

	Below p50			Over p50		
	Adj. gender gap	sh_female	BS	Adj. gender gap	sh_female	BS
BS (averagebonus share)	-1.043***	-1.254***		-0.122***	-0.133	
	(0.112)	(0.187)		(0.047)	(0.633)	
firm_fe (γ)	0.037***	-0.029***		0.089***	-0.052***	
	(0.006)	(0.010)		(0.006)	(0.008)	
sh_female	-0.141***			-0.093***		
	(0.020)			(0.034)		
sh_tert		-0.003			0.018***	
		(0.007)			(0.007)	
sh_part		0.232***			0.212***	
		(0.011)			(0.011)	
sh_temp		0.004			0.030***	
		(0.005)			(0.010)	
inn_firm			0.011***			0.001
			(0.001)			(0.004)
nocollbarg			-0.012***			-0.017***
			(0.001)			(0.002)
sh_manager			0.055***			0.029***
			(0.004)			(0.005)
d_fem_manager	0.006***	0.052***	0.000	-0.003	0.048***	0.005***
	(0.002)	(0.003)	(0.001)	(0.003)	(0.006)	(0.001)
av_tenure	0.003***	0.003***	0.002***	-0.000	-0.000	0.002***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.002)	(0.000)
public	-0.009***	0.024***	-0.007***	-0.019***	0.024***	-0.007***
	(0.003)	(0.004)	(0.001)	(0.003)	(0.006)	(0.002)
fsize (medium)	0.011***	0.010***	0.009***	-0.000	-0.003	0.013***
	(0.002)	(0.004)	(0.001)	(0.003)	(0.010)	(0.001)
fsize (large)	0.018***	0.024***	0.016***	-0.020***	-0.024	0.026***
	(0.003)	(0.005)	(0.001)	(0.003)	(0.018)	(0.001)
sh_high_occup	0.029***	0.069***	0.026***	0.019***	-0.032*	0.024***
	(0.006)	(0.010)	(0.002)	(0.004)	(0.018)	(0.003)
Constant	0.163***	0.314***	0.073***	0.050**	0.307***	0.064***
	(0.024)	(0.025)	(0.008)	(0.022)	(0.042)	(0.007)
Year/country/region/ industries dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85,977	85,977	85,977	56,274	56,274	56,274

Notes: Standard errors, clustered at industry/country/year/ region, are reported in parentheses. All equations include region, industry, country, year and country*year effects.
***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table A10 Split sample analysis: effects of IPS on the adjusted gender wage gap in sectors with low and high intensity of intangible capital (training)

	Below p50			Over p50		
	Adj. gender gap	sh_female	BS	Adj. gender gap	sh_female	BS
BS (average bonus share)	-0.680***	-1.233***		-0.644**	-0.554**	
	(0.159)	(0.223)		(0.286)	(0.250)	
firm_fe (γ)	0.052***	-0.009		0.065***	-0.054***	
	(0.006)	(0.010)		(0.006)	(0.007)	
sh_female	-0.148***			-0.145***		
	(0.023)			(0.025)		
sh_tert		0.014*			-0.001	
		(0.008)			(0.006)	
sh_part		0.217***			0.267***	
		(0.011)			(0.012)	
sh_temp		0.005			0.030***	
		(0.005)			(0.009)	
inn_firm			0.009***			0.005***
			(0.001)			(0.002)
nocollbarg			-0.011***			-0.017***
			(0.001)			(0.002)
sh_manager			0.057***			0.025***
			(0.005)			(0.006)
d_fem_manager	0.009***	0.057***	0.002***	0.006**	0.051***	0.004***
	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)
av_tenure	0.002***	0.004***	0.002***	0.001	0.000	0.002***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
public	-0.008***	0.019***	-0.005***	-0.020***	0.022***	-0.008***
	(0.003)	(0.004)	(0.001)	(0.004)	(0.005)	(0.002)
fsize (medium)	0.007**	0.015***	0.009***	0.004	-0.001	0.013***
	(0.003)	(0.004)	(0.001)	(0.005)	(0.005)	(0.001)
fsize (large)	0.011***	0.027***	0.015***	-0.009	-0.012	0.025***
	(0.004)	(0.005)	(0.001)	(0.009)	(0.008)	(0.001)
sh_high_occup	0.022***	0.042***	0.023***	0.030***	0.013	0.027***
	(0.007)	(0.011)	(0.002)	(0.010)	(0.010)	(0.002)
Constant	0.158***	0.308***	0.078***	0.113***	0.335***	0.064***
	(0.034)	(0.044)	(0.017)	(0.029)	(0.021)	(0.005)
Year/country/region/ industries dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,810	75,810	75,810	66,441	66,441	66,441

Notes: Standard errors, clustered at industry/country/year/ region, are reported in parentheses. All equations include region, industry, country, year and country*year effects.
***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

List of Tables

List of Figures

UNTANGLED Partners:

KU LEUVEN HIVA RESEARCH INSTITUTE FOR WORK AND SOCIETY

LUXEMBOURG INSTITUTE OF SOCIO-ECONOMIC RESEARCH

ibs institute for structural research

wiiw

ESRI ECONOMIC & SOCIAL RESEARCH INSTITUTE

POLITECNICO MILANO 1863

IPLE

FEDESARROLLO Centro de Investigación Económica y Social

DPRU DEVELOPMENT POLICY RESEARCH UNIT

ZENTRUM FÜR SOZIALE INNOVATION CENTRE FOR SOCIAL INNOVATION ZSI

unipg UNIVERSITÀ DEGLI STUDI DI PERUGIA

LÉO Laboratoire d'Économie d'Orléans

RWI

ALDGATE STRATEGY GROUP

UNTANGLED is a three-year interdisciplinary Horizon 2020 research project that seeks to examine the interconnected trends of globalisation, demographic change and technological transformation, and their effects on labour markets in the European Union and beyond. By engaging a broad range of stakeholders, including companies and civil society organisations, we will develop practical policy proposals to help governments cushion the negative impacts of these trends and ensure their benefits are enjoyed fairly across regions and sectors.

Follow us on social media:

twitter.com/untangledEU

facebook.com/UntangledEU

linkedin.com/company/project-untangled-eu

www.projectuntangled.eu