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ABSTRACT

The Heterogeneous Effects of Workforce Diversity on Productivity, Wages and Profits[*]

We estimate the impact of workforce diversity on productivity, wages and productivity-wage gaps (i.e. profits) using detailed Belgian linked employer-employee panel data. Findings, robust to a large set of covariates, specifications and econometric issues, show that educational (age) diversity is beneficial (harmful) for firm productivity and wages. The consequences of gender diversity are found to depend on the technological/knowledge environment of firms. While gender diversity generates significant gains in high-tech/ knowledge intensive sectors, the opposite result is obtained in more traditional industries. Overall, findings do not point to sizeable productivity-wage gaps except for age diversity.

JEL Classification: D24, J24, J31, M12

Keywords: labour diversity, productivity, wages, linked panel data, GMM

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1. Introduction

Efficient management of human resources (HR) is a key issue for firms' economic success. It does not only consist in dealing appropriately with single workers' demands, bureaucratic procedures or institutional settings. Properly managing HR also (and perhaps mostly) implies finding the right workforce mix and to make the most of workers' skills. A diverse workforce, with respect to education, experience or physical stamina, is often needed due to the variety of tasks that have to be performed within firms. Labour diversity may also benefit firm productivity if it fosters complementarities (e.g. between high- and low-skilled workers), generates spillovers (e.g. knowledge transfers between more and less experienced workers), makes the workplace more enjoyable (e.g. educational/skills diversity could be appreciated by employees) or stimulates demand (e.g. customers may prefer companies that have a diverse workforce).[1] The downside of diversity, however, is that it may lead to misunderstandings, communication problems, personal conflicts or negative reactions from stakeholders that undermine performance (Akerlof and Kranton, 2000; Becker, 1957; Choi, 2007; Kremer, 1993; Lazear, 1999).

Today's labour force is getting more and more heterogeneous: ageing, migration, women's increased labour participation and technological change are key drivers of this phenomenon (Ilmakunnas and Ilmakunnas, 2011; Kurtulus, 2012; Parrotta et al, 2012a). Moreover, in many countries companies are under legislative pressure to diversify their workforce either through quotas or affirmative action. Workforce diversity has thus become an essential business concern. Firms have to manage diversity both internally (i.e. among management and staff) and externally (i.e. by addressing the needs of diverse customers, suppliers or contractors). As a result, an increasing number of firms employ a 'diversity manager' whose task is to ensure that diversity does not hamper productivity but may contribute to the attainment of the firm's objectives. From the workers' point of view, labour diversity may also generate benefits or losses. The latter may be the result of a more (or less) enjoyable working environment, but they may also derive from a higher (or lower) wage. According to competitive labour market theory, workers are paid at their marginal revenue products. Hence, if labour diversity affects productivity, it may also influence workers' earnings.

The empirical evidence regarding the impact of labour diversity on productivity is very inconclusive. Moreover, findings must often be interpreted with caution because of methodological and/or data limitations. In addition, studies on the wage effects of diversity are almost non-existent

[1] In the HR literature, "diversity management" refers to policies and practices that seek to include people within a workforce who are considered to be, in some way, different from those in the prevailing constituency. It usually refers to dimensions such as gender, age, sexual orientation, religion, ethnicity, social origin and physical appearance.

(as far as we know, Ilmakunnas and Ilmakunnas (2011) is the only exception). Finally, only few papers examine whether the diversity-productivity nexus is influenced by specific working environments. However, from the point of view of maximizing productivity, the optimal degree of diversity is likely to depend on the nature of the production unit and its technology (Lazear, 1999). For instance, it has been argued that traditional industries, which are essentially characterized by routine tasks, might be better off with a more homogeneous workforce (Pull et al., 2012). In contrast, high-technology/knowledge-intensive sectors may benefit more from diversity as it stimulates creative thinking and innovation (Arun and Arun, 2012; Parrotta et al., 2012b).

The aim of this paper is threefold. First, we put the relationship between labour diversity (measured through education, age and gender) and firm productivity to an updated test, taking advantage of access to detailed Belgian linked employer-employee (hereafter LEE) panel data for the years 1999-2006. These data offer several advantages. On the one hand, the panel covers a large part of the private sector, provides accurate information on average productivity (i.e. on the average value added per hour worked) and allows to control for a wide range of worker and firm characteristics (such as education, age, sex, tenure, occupations, working time, labour contracts, firm size, capital stock and sector of activity). On the other hand, it enables to compute various diversity indicators and to address important methodological issues such as firm-level invariant heterogeneity and endogeneity (using both the generalized method of moments (GMM) and Levinsohn and Petrin (2003) estimators). Secondly, we examine how the benefits or losses of labour diversity are shared between workers and firms. Therefore, we estimate the impact of labour diversity respectively on mean hourly wages and productivity-wage gaps (i.e. profits)[2] at the firm level. Finally, we investigate whether the diversity-productivity-wage nexus varies across working environments. More precisely, we test the interaction with the degree of technological and knowledge intensity of sectors. Therefore, we rely on three complementary taxonomies of industries developed by Eurostat (2012) and by O'Mahony and van Ark (2003).

The remainder of this paper is organized as follows. A review of the literature is presented in the next section. Sections 3 and 4 respectively describe our methodology and data set. The impact of workforce diversity on productivity, wages and productivity-wage gaps across heterogeneous knowledge/technological environments is analysed in Section 5. The last section discusses the results and concludes.

[2] By definition, the gap between productivity and wages corresponds to the gross operation surplus (i.e. profits).

2. Review of the literature

2.1. Workforce diversity and firm productivity

There are different economic forces underlying the relationship between workforce diversity and productivity.[3] As highlighted by Alesina and La Ferrara (2005), these forces may derive from: individual *preferences* (either people may attribute positive (negative) utility to the well-being of members of their own group (of other groups) or they may value diversity as a social good), individual *strategies* (even when people have no taste for or against diversity, it may be more efficient, notably in the presence of market imperfections, to interact preferably with members of one's own group)[4], or the characteristics of the *production function* (i.e. the complementarity in people's skills).[5]

Lazear (1999) follows the production function approach and develops a theoretical model in which a global (i.e. multinational) firm is presented as a diverse (i.e. multi-cultural) team. He argues that labour diversity is beneficial for firm performance if skills and information sets are group- (i.e. culture-) specific. More precisely, he demonstrates theoretically that the gains from diversity are greatest when three conditions are fulfilled: a) individuals have completely different (i.e. disjoint) skills and information sets, b) the latter are all relevant for the tasks that have to be performed within the firm, and c) individuals are able to communicate with (i.e. to understand) each other.

Young workers are thought to learn faster (Skirbekk, 2003) and to have better cognitive and physical abilities (Hoyer and Lincourt, 1998), while older workers are typically considered to have more job experience and knowledge about intra-firm structures, relevant markets and networks (Czaja and Sharit, 1998; Grund and Westergaard-Nielsen, 2008). Given that these complementary skills are relevant for most firms, Lazear's (1999) model suggests that age diversity may generate some gains. However, the net effect on productivity will only be positive if these gains outweigh additional communication costs (and difficulties related to emotional conflicts) incurred by a more

[3] Given the focus of our paper, this section essentially reviews the literature regarding the productivity effects of age, educational and gender diversity.

[4] Osborne (2000), for instance, builds a model, with full information regarding both the supply and demand-side of the market, to examine workforce-diversity patterns of profit-maximizing firms. His model shows that the optimal degree of labour force mix depends on the diversity in groups' physical productivity but also on demand-side factors, i.e. the characteristics of the product that is sold, the extent to which different markets value them, and the extent to which groups intrinsically vary in their capacity to provide them. To illustrate this conclusion, Osborne provides the example of police officers of specific ethnic groups that may be better suited to patrol neighbourhoods essentially populated by those groups. Conversely, he notes that the ethnicity of an automobile worker who installs the clutch is unlikely, ceteris paribus, to affect his productivity and the consumers' willingness to buy the car.

[5] The variety of ways in which people interpret problems and use their cognitive skills to solve them, may be an important source of innovation and productivity (Parrotta et al., 2012b).

diverse workforce. It has repeatedly been argued (see e.g. Lazear, 1999; Jehn et al., 1999) that this condition is unlikely to be satisfied for demographic diversity (heterogeneity in terms of age, gender or ethnicity) but may well be fulfilled for educational (i.e. task-related) heterogeneity. The latter may indeed enhance efficiency if there is sufficient mutual learning and collaboration among workers with different educational backgrounds (Hamilton et al., 2004).

Kremer (1993) develops the O-ring production function based on the assumption that quantity and quality of labour cannot be substituted. The underlying intuition is that many production processes involve a large number of tasks and that a small failure in one of these tasks may lead to a strong decrease in production value. Kremer gives the example of a company that may go bankrupt due to bad marketing, even if product design, manufacturing and accounting are excellent.[6] With this type of production function, it can be shown that profit-maximizing firms should match workers of similar skills/education together. Task-related heterogeneity would thus hamper productivity.

Social cognitive theory examines how the efficacy of a group (i.e. “a group’s belief in their conjoint capabilities to organize and execute the courses of action required to produce given levels of attainments” (Bandura, 1997, p. 477)) affects its performance. Results suggest that collective efficacy is not always beneficial for the outcome of a group. Moreover, mixed gender groups are found to foster the impact of group efficacy on performance (Lee and Farh, 2004). The argument is that gender diversity is likely to increase the heterogeneity in the values, beliefs and attitudes of the members of a group, which in turn may stimulate critical thinking and prevent the escalation of commitment (i.e. inflated perception of group efficacy resulting in poor decision making).

Conclusions regarding the optimal workforce mix are somewhat different if one follows the organizational demography or social comparison literature. The former (see e.g. Pfeffer, 1985) stresses the importance of social similarity (and thus of inter-personal attraction) to stimulate interaction, communication and cohesion among the workforce. Given that features such as age, education or gender help to explain similarity, diversity along these dimensions is expected to hamper job satisfaction, communication and firm performance. Social comparison theory (Festinger, 1954) posits that people evaluate and compare their opinions and abilities with those of similar others (e.g. individuals of the same age, education or gender). Moreover, it puts forward that people try to perform better than the members of their comparison group (Pelled et al., 1999), which in turn leads to rivalry and conflicts likely to undermine performance (Choi, 2007). From this perspective, labour diversity may benefit the organisation. However, as highlighted by Grund and Westergaard-Nielsen (2008), a decision might be of better quality when it is the outcome of a confrontation between

[6] The title of his paper refers to the space shuttle Challenger that exploded because of a slight imperfection in a single component, called the O-rings.

rivals' views. Various theories, such as tournaments (Lazear and Rosen, 1981), suggest in addition that rivalry among similar workers may be good for performance as it encourages workers to produce more effort.

2.2. Traditional versus high-tech/knowledge intensive sectors

Productivity effects of workforce diversity are likely to vary across working environments. Several authors suggest in particular that they may differ between high-tech/knowledge intensive sectors and more traditional industries.

Prat (2002), for instance, uses team theory to address the problem of optimal labour diversity. His model predicts that workforce homogeneity should be preferred in the presence of positive complementarities, i.e. when coordination of actions between the various units of a company is of prime importance. In contrast, labour diversity would be beneficial in the case of negative complementarities, i.e. when workers' actions are substitutes in the firm's payoff function. To illustrate this situation, Prat (2002) gives the example of a firm whose activity is based on the exploitation of new opportunities and the development of successful innovations. Given that a firm's likelihood to innovate is expected to be greater if researchers do not all have the same skills and information sets, some degree of dissimilarity should indeed be optimal. To put it differently, provided that workforce diversity increases the set of ideas and potential solutions to a given problem, it may foster the innovative capacity of firms and hence their productivity (Parrotta et al., 2012b).

These predictions are largely in line with those of Jehn et al. (1999). The latter argue that group performance is more likely to benefit from educational (i.e. task-related) diversity if the tasks that have to be accomplished within a group are complex rather than routine. They also show that age and gender diversity are potentially more disruptive when members of a group depend on each other to complete their jobs (i.e. in the presence of positive complementarities). Overall, these results suggest that the benefits of diversity are more likely to outweigh the costs in high-tech/knowledge intensive sectors than in traditional industries, particularly if the former (latter) are characterized by complex (routine) tasks, negative (positive) complementarities and innovative (functional) output.

Akerlof and Kranton (2000) introduce the concept of identity (i.e. a person's sense of self) into an economic model of behaviour to study how identity influences economic outcomes. Taking gender as an illustration of identity, the authors highlight that social categories such as 'men' and 'women' are associated to prescribed behaviours and ideal physical characteristics. More precisely, the identity of one's self would be shaped by the behavioural prescriptions associated to the social category to which a person belongs and the infringement of these prescriptions would generate anxiety in oneself and others. As an example, given that a dress is a typical symbol of femininity, the authors point out that men are generally not willing to wear a dress and that the departure from this behaviour may threaten the identity of other men. In the context of work, they argue that a woman doing a "man's" job (e.g. truck driver or carpenter) may deteriorate the self-image of her male co-workers. Indeed, the latter may feel less masculine, be afraid that other men will make fun of them or fear that people will think that fewer skills are needed for their occupation if a woman is doing the same job. As a result, women in male-dominated occupations might suffer from a strong hostility and be discriminated against by their male counterparts.[7] Put differently, Akerlof and Kranton (2000) suggest that the utility of people joining a group (e.g. an occupation or a firm) depends positively (negatively) on the proportion of group members of the same (of a different) social category. Moreover, they predict that increasing gender diversity may negatively affect firm performance, especially if men constitute a socially 'dominant' group (Haile, 2012). Under the hypothesis that the workforce is less gender-balanced and the environment more 'macho' in traditional companies than in high-tech/knowledge intensive firms, the above arguments suggest that gender diversity will have a less favorable impact on performance in the former group of companies. This prediction could also be supported by the fact that high-tech/knowledge intensive sectors rely increasingly on inter-personal or 'soft' skills (that might be more effectively provided by women) and require generally less physical stamina than traditional (private sector) firms, e.g. construction companies (Arun and Arun, 2002; Webster, 2007).

2.3. Previous empirical studies

Harrison and Klein (2007: 1199) emphasized some years ago that empirical evidence regarding the performance effects of workforce diversity is "weak, inconsistent or both". This statement remains to a large extent valid. Indeed, findings are still quite inconclusive and often difficult to interpret due to methodological and/or data limitations.

A number of papers in the HRM, sociology and psychology literatures investigate the impact of labour diversity (with respect to e.g. education, age, gender, race, sexual orientation, disability) on various outcomes at the worker (e.g. organizational commitment, turnover, creativity, frequency of

[7] The same reasoning could be applied to men employed in female-dominated occupations (e.g. nursing, primary school teaching). However, given that our empirical analysis relies on data from the private sector and that female-dominated occupations are more frequent in the public sector, we essentially focus on why gender diversity might have a different influence on organizational performance when men constitute a socially 'dominant' group.

communication) and company (e.g. financial indicators, ratings of group effectiveness) level.[8] Many of these field and experimental studies, however, rely on "small samples of workers in narrow occupational fields that often lack a longitudinal component" (Kurtulus, 2011: 685). Moreover, almost none of these analyses control for reverse causality. In this section, for the sake of brevity and methodological comparability, we focus on the relatively few studies that have been undertaken by economists and that address the productivity effects of (at least one of) the diversity dimensions (i.e. education, age and gender) investigated in this paper.[9]

Results based on personal records from single companies

A first strand of the economic literature analyzes the diversity-performance nexus using case studies, i.e. personal records from single companies. The advantage of this approach is that it enables to control for very detailed worker characteristics and *de facto* for firm time-invariant unobserved heterogeneity. However, focusing on data from a single company is likely to reduce the external validity of the results.

Hamilton et al. (2004) use weekly data from a Californian garment manufacturing plant for the years 1995-1997. Their results indicate that teams with greater diversity in workers' abilities and composed of only one ethnicity (namely Hispanics) are more productive (i.e. sew more garments per day). In contrast, team heterogeneity in workers' age is found to decrease productivity. Yet, results for team demographics (age and ethnicity) should be taken with care as they become insignificant when applying fixed effects (FE). Leonard and Levine (2006) rely on longitudinal data (collected in 1996-1998) from a low-wage service-sector employer with establishments (retail stores or restaurants) throughout the U.S. They study the influence of demographic (race, gender and age) diversity between a workgroup and its customers and within a workgroup on an indirect measure of productivity, namely individual turnover within workgroups. Results (controlling for individual FE) show that diversity does not consistently predict turnover. In contrast, isolation (i.e. being in a numerical minority) from co-workers and customers, especially with respect to race, often leads to higher turnover. Mas and Moretti (2009) investigate how the productivity of cashiers in a large supermarket chain in the U.S. is affected by their peers. Using high-frequency data between 2003 and 2006, they find evidence of positive spillovers from the introduction of highly productive workers (i.e. workers scanning a large number of items per second) in a shift. More precisely, first-

[8] For a review see e.g. Horwitz and Horwitz (2007), Ilmakunnas and Ilmakunnas (2011) and Roberge and van Dick (2010).
[9] Results from field experiments conducted by economists (see e.g. Hoogendoorn et al., 2011) are not surveyed as they are less directly comparable to our findings and because of the space constraint.

difference estimates show that less (more) capable workers become significantly more productive in the presence (are not affected by the presence) of highly (less) productive co-workers. Skill diversity within shifts is thus found to increase productivity. Kurtulus (2011) uses detailed personal records of a large U.S. firm in the health service industry for the years 1989-1994. Her FE estimates highlight that diversity within organisational divisions with respect to age, firm tenure, and performance is associated with lower worker's productivity (i.e. subjective performance evaluated by managers). In contrast, worker's performance would be boosted by intra-division differences in wages.

Results based on linked employer-employee data

Another strand of the literature relies on linked employer-employee data (LEED). These data have the advantage of being representative of a large part of the economy. Moreover, merged to firm-level accounting data, they allow to estimate the impact of labour diversity on quite precise measures of plant- or firm-level productivity (e.g. total factor productivity (TFP) or value-added) while controlling for a large set of worker and employer characteristics.

Barrington and Troske (2001) examine the impact of plant-level diversity (with respect to age and gender) on plant-level productivity (i.e. value-added and sales per worker and TFP) respectively in the manufacturing, retail trade and services industry. Based on cross-sectional LEED for 1999, their OLS estimates reject the hypothesis that workforce diversity would be detrimental for the productivity of U.S. plants. Grund and Westergaard-Nielsen (2008) use LEED for the Danish private sector over the period 1992-1997. They find (with a FE estimator) that firms with a medium age dispersion perform best (i.e. obtain the highest value-added and profits per employee).

The studies of Iranzo et al. (2008), Navon (2009), Ilmakunnas and Ilmakunnas (2011) and Parrotta et al. (2012a) are more directly comparable to our investigation as they do not only control for firm time-invariant unobserved heterogeneity but also for endogeneity. Iranzo et al. (2008) examine how productivity (measured by firm-level value-added) is influenced by the intra-firm dispersion in workers' skills (proxied by workers' FE estimated from an individual wage regression). Using LEED from the Italian manufacturing industry over the period 1981-1997, their results (based respectively on the estimation methods developed by Olley and Pakes (1996, hereafter OP) and Ackerberg et al. (2006, hereafter ACF)) show that intra-firm skill dispersion within (between) occupational groups – production and non production workers – is beneficial (detrimental) for firm productivity. Moreover, they find no differences in estimation results when splitting firms according to whether they belong to an ICT or non-ICT industry (following the taxonomy proposed by O'Mahony and van Ark (2003)). Navon (2009) relies on LEED for the Israeli manufacturing industry over the period 2000-2003. Controlling for plant FE and endogeneity (using the OP and Levinsohn and Petrin (2003, hereafter LP) semi-parametric estimation techniques), he finds that within-plant educational diversity among higher educated workers (i.e. the variability in academic disciplines in which the latter obtained their university degrees) is beneficial for plant-level value-added. Ilmakunnas and Ilmakunnas (2011) investigate whether firms and employees benefit from diversity using Finnish LEED covering the industrial sector (i.e. mining, manufacturing, energy and construction) for the years 1990-2004. Plant-level regressions (estimated with FE, generalized methods of moments (GMM) and OP estimators) show that TFP depends positively (negatively) on age (educational) diversity. In contrast, the latter variables turn out to be statistically insignificant when the authors estimate individual wage regressions. Parrotta et al. (2012a) use register-based LEED covering most of the Danish private sector between 1995 and 2005. Their results, based on the ACF approach, show that diversity in education (ethnicity, age and gender) enhances (deteriorates) firm's value added. Moreover, dividing industries into two groups according to their aggregate level of R&D expenditures, they find no evidence that the impact of diversity would be different for firms in high-tech industries (i.e. in industries with above-average R&D expenditures), although the latter are typically thought to require more creative thinking and problem-solving skills.[10]

In sum, to our knowledge, only four papers investigate the impact of educational, age and/or gender diversity on firm productivity using large representative data and controlling for time-invariant firm unobserved heterogeneity and endogeneity. These studies disagree on whether age and educational diversity are beneficial or harmful for firm productivity. Moreover, estimates concerning the influence of gender diversity are only provided by Parrotta et al. (2012a).[11] As regards the study of Ilmakunnas and Ilmakunnas (2011), it is the only one that extends the analysis to workers' wages, i.e. that analyses how the benefits or losses of labour diversity are shared between workers and firms. Last but not least, there is surprisingly little evidence on whether the diversity-productivity relationship varies across working environments. Our paper contributes to this literature by investigating how diversity (with respect to education, age and gender) affects productivity, wages and productivity-wage gaps at the firm level. We also examine how the diversity-productivity-wage

[10] In a companion paper, Parrotta et al. (2012b) merge the Danish LEED set with information on firms' innovation ability for the years 1995-2003. Using an instrumental variable approach, they find that ethnic diversity within firms is valuable for the latter's innovative outcomes. In contrast, educational, age and gender diversity turn out to be statistically insignificant. Based on similar data for the period 1980-2002 and controlling for endogeneity, Marino et al. (2012) show in addition that intra-firm diversity in terms of education and ethnicity (age and gender) increases (decreases) workers' transition probability from employment to self-employment, i.e. their propensity to become entrepreneurs.

[11] A few recent papers (e.g. Vandenberghe, 2011), testing for gender wage discrimination, investigate with LEED how the share of women within firms influences the latter's productivity and labour costs. Yet, results from these studies are not straightforward to interpret from a diversity perspective. Indeed, whether a growing share of women corresponds to more or less gender diversity depends on the initial intra-firm proportion of women.

nexus varies according to the technological/knowledge environment of firms. To do so, we rely on longitudinal LEED from the Belgian private sector, use various diversity indicators, control for a large set of covariates, implement both GMM and LP estimation techniques, and assess the technological/knowledge intensity of firms through various complementary taxonomies.

3. Methodology

The empirical results presented in this paper are based on the separate estimation of a value added function and a wage equation at the firm level. The latter provide parameter estimates for the impact of labour diversity (with respect to education, age and gender) on average productivity and wages, respectively. Given that both equations are estimated on the same samples with identical control variables, the parameters for marginal products and wages can be compared and conclusions can be drawn on how the benefits or losses of diversity are shared between workers and firms. This technique was pioneered by Hellerstein and Neumark (1995) and refined by Hellerstein et al. (1999), Hellerstein and Neumark (2004), Aubert and Crépon (2009) and van Ours and Stoeldraijer (2011). It is now standard in the literature on the productivity and wage effects of labour heterogeneity (see e.g. Cataldi et al. 2012; Göbel and Zwick 2012; Vandenberghe 2012).

The estimated firm-level productivity and wage equations are the following:

$$\log\left(\frac{Value\ Added}{Hours}\right)_{i,t} = \alpha + \beta_1 A^{\sigma}_{i,t} + \beta_2 E^{\sigma}_{i,t} + \beta_3 G^{\sigma}_{i,t} + \beta_4 \overline{A}_{i,t} + \beta_5 \overline{E}_{i,t} + \lambda X_{i,t} + \varepsilon_{i,t} \qquad (1)$$

$$\log\left(\frac{Total\ Wages}{Hours}\right)_{i,t} = \alpha^* + \beta^*_1 A^{\sigma}_{i,t} + \beta^*_2 E^{\sigma}_{i,t} + \beta^*_3 G^{\sigma}_{i,t} + \beta^*_4 \overline{A}_{i,t} + \beta^*_5 \overline{E}_{i,t} + \lambda^* X_{i,t} + \varepsilon^*_{i,t} \qquad (2)$$

The dependent variable in equation (1) is firm *i*'s hourly added value, obtained by dividing the total added value (at factor costs) of the firm *i* in period *t* by the total number of work hours (taking into account paid overtime hours) that have been declared for the same period. The dependent variable in equation (2) is firm *i*'s average hourly gross wage (including premia for overtime, weekend or night work, performance bonuses, commissions, and other premia). It is obtained by dividing the firm's total wage bill by the total number of work hours. Hence, the dependent variables in the estimated equations are firm averages of added value and wage on an hourly basis.

Labour diversity indicators with respect to education, age and gender (E^{σ}, A^{σ} and G^{σ}) are the main variables of interest. A theoretical model justifying the inclusion of diversity indicators, on top of mean values, in a firm-level productivity equation is provided by Iranzo et al. (2008). The firm-level standard deviation and *average* dissimilarity index are respectively used to measure diversity.[12] The standard deviation of workforce characteristics (education, age and gender) reflects group diversity (as it takes the same value for all workers within a firm), while the dissimilarity index (also called Euclidean distance) refers to relational demography (Ilmakunnas and Ilmakunnas, 2011). It measures the degree to which a worker differs from his peers within a firm. Its value thus depends on the distance between a worker's characteristic and the mean value of the latter within a firm. The *average* dissimilarity index corresponds to the firm-level average over all workers of the individual-level dissimilarity index. More precisely, if $E_{i,j}$ corresponds to the number of years of education of worker i in firm j and the total employment in firm j is equal to N_j, than the dissimilarity index for worker i in firm j is computed as follows:

$$Dissimilarity(Education)_{i,j} = \sqrt{N_j^{-1}\sum_{k=1}^{N_j}\left(E_{i,j} - E_{k,j}\right)^2} = \sqrt{\left(E_{i,j} - \overline{E}_j\right)^2 + Var\left(E_j\right)} \qquad (3)$$

and the *average* dissimilarity index at firm j is given by:

$$Dissimilarity(Education)_j = N_j^{-1}\sum_{i=1}^{N_j}\sqrt{N_j^{-1}\sum_{k=1}^{N_j}\left(E_{i,j} - E_{k,j}\right)^2} \qquad (4)$$

In addition to the firm-level standard deviation and average dissimilarity index of workers' education, age and gender, we also compute an alternative gender diversity index, i.e. the share of women times the share of men within firms (Hoogendoorn et al., 2011). This indicator, as well as the others, has the property that diversity is maximal when workers are equally distributed across groups (e.g. when proportions of men and women are equal) and minimal when all workers belong to the same group (e.g. when the workforce is only composed of women or men).

In line with earlier empirical work, we also add workers' average age and education at the firm-level ($\overline{E}$ and $\overline{A}$) among regressors in equations (1) and (2).[13] Other control variables are included in the vector X. The latter contains the share of part-time workers, the fraction of workers with a fixed-term employment contract, the proportion of employees with at least 10 years of tenure,

[12] To avoid multicolinearity problems, these variables are included separately in the regressions.
[13] We do not include the share of women as it creates multicolinearity with gender diversity indices.

the percentage of white-collar workers, firm size (i.e. the number of employees) and capital stock[14], 8 industry dummies, and 7 year dummies.[15]

Estimating equations (1) and (2) allows gauging the effect of labour diversity on firm productivity and wages, but it does not allow testing directly whether the difference between the value added and the wage coefficients for a given diversity indicator is statistically significant. A simple method to obtain a test for the significance of productivity-wage gaps has been proposed by van Ours and Stoeldraijer (2011). We apply a similar approach and estimate a model in which the *difference* between firm *i*'s hourly value added and hourly wage (i.e. the hourly gross operating surplus) is regressed on the same set of explanatory variables as in equations (1) and (2). This produces coefficients for the diversity indicators and directly measures the size and significance of their respective productivity-wage gaps.

Equations (1) and (2), as well as the productivity-wage gap, can be estimated with different methods: pooled ordinary least squares (OLS), a fixed-effect (FE) model, the generalized method of moments (GMM) estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998), or a more structural approach suggested by Levinsohn and Petrin (2003, hereafter LP). This being said, pooled OLS estimators of productivity models have been criticized for their potential "heterogeneity bias" (Aubert and Crépon 2003: 116). This bias is due to the fact that firm productivity depends to a large extent on firm-specific, time-invariant characteristics that are not measured in micro-level surveys. As a consequence, OLS regression coefficients associated to diversity variables will be biased since unobserved firm characteristics may affect simultaneously the firm's added value (or wage) and the composition of its workforce. This is referred to as a problem of spurious correlation and could be caused by factors such as an advantageous location, firm-specific assets like the ownership of a patent, or other firm idiosyncrasies.

One way to remove unobserved firm characteristics that remain unchanged during the observation period is by estimating a FE model. However, neither pooled OLS nor the FE estimator address the potential endogeneity of our explanatory variables. Yet, labour diversity is likely to be endogenous. Indeed, any shock in wages or in productivity levels might generate correlated changes in the firm's workforce and in labour productivity that are not due to changes in the firm's workforce composition *per se*. For instance, one might expect that a firm undergoing a negative productivity shock would prefer not to hire new individuals, which would increase the age of the workforce and

[14] It is estimated through the "perpetual inventory method" (or PIM, see OECD (2009) for more details). The PIM rests on the simple idea that the capital stock results from investment flows (available in our data) after correction for retirement and efficiency loss. Following standard practice, we assume a 5 percent annual rate of depreciation of capital.

[15] All independent variables are measured in terms of shares in total work hours. For instance, the fraction of part-time workers is computed on the basis of the proportion of hours worked by employees working less than 30 hours per week over the total amount of hours worked with the firm.

affect the age diversity index. Similarly, during economic downturns, firms may be more likely to reduce personnel among women and less educated workers as adjustments costs are often lower for these categories of workers (due to e.g. their lower wages and/or tenure). In order to control for this endogeneity issue and for the presence of firm fixed effects, we estimated our model using the system GMM (GMM-SYS) and LP estimators, respectively.

The GMM-SYS approach boils down to simultaneously estimating a system of two equations (one in level and one in first differences) and to relying on 'internal instruments' to control for endogeneity. More precisely, diversity variables[16] in the differenced equation are instrumented by their lagged levels and diversity variables in the level equation are instrumented by their lagged differences. The implicit assumption is that changes (the level) in (of) the dependent variable – productivity or wages – in one period, although possibly correlated with contemporaneous variations (levels) in (of) diversity variables, are uncorrelated with lagged levels (differences) of the latter. Moreover, changes (levels) in (of) diversity variables are assumed to be reasonably correlated to their past levels (changes). One advantage of GMM-SYS is that time-invariant explanatory variables can be included among the regressors, while the latter typically disappear in difference GMM. Asymptotically, the inclusion of these variables does not affect the estimates of the other regressors because instruments in the level equation (i.e. lagged differences of diversity variables) are expected to be orthogonal to all time-invariant variables (Roodman, 2009). In order to find the correctly specified model, we start with the moment conditions that require less assumptions and increase the number of instruments progressively (Göbel and Zwick, 2012). To examine the validity of additional instruments, we apply the Hansen (1982) test of over-identifying restrictions. In addition, Arellano-Bond (1991) test for serial correlation (i.e. for second-order autocorrelation in the first differenced errors) is used to assess whether estimates are reliable. Practically, we choose the model with the lowest number of lags that passes the Hansen and Arellano-Bond tests.

Our second approach to tackle endogeneity and firm fixed effects in the productivity equation is the semi-parametric estimation method proposed by LP. This broadly used method, particularly well suited for panels with small t and big N, boils down to estimating a value added function with material inputs (i.e. inputs – such as energy, raw materials, semi-finished goods, and services – that are typically subtracted from gross output to obtain value added) as instruments.[17] The underlying

[16] By 'diversity variables', we mean diversity variables *stricto sensu* and other endogenous input factors.
[17] The LP estimation procedure, when using diversity indicators as main explanatory variables, differs somewhat from the standard setup. More details can be found in Ilmakunnas and Ilmakunnas (2011: 252-253).

assumption is that firms respond to time-varying productivity shocks observed by managers (and not by econometricians) through the adjustment of their intermediate inputs.[18]

4. Data and descriptive statistics

Our empirical analysis is based on a combination of two large data sets covering the years 1999-2006. The first, carried out by Statistics Belgium, is the 'Structure of Earnings Survey' (SES). It covers all firms operating in Belgium which employ at least 10 workers and with economic activities within sections C to K of the NACE Rev.1 nomenclature.[19] The survey contains a wealth of information, provided by the management of firms, both on the characteristics of the latter (e.g. sector of activity, number of workers) and on the individuals working there (e.g. age, education, sex, tenure, gross earnings, paid hours, occupation).[20] The SES provides no financial information. Therefore, it has been merged with a firm-level survey, the 'Structure of Business Survey' (SBS). The SBS, also conducted by Statistics Belgium, provides information on financial variables such as firm-level material inputs, investments, value added and gross operating surplus. The coverage of the SBS differs from that of the SES in that it does not cover the whole financial sector (NACE J) but only Other Financial Intermediation (NACE 652) and Activities Auxiliary to Financial

[18] The LP approach is an extension of the Olley and Pakes (1996) estimation strategy. The latter uses investments (rather than intermediate inputs) as instruments which presents some drawbacks. In particular, LP have argued that investments respond less smoothly to productivity shocks (than intermediate inputs) due to considerable adjustments costs. Moreover, the OP approach implies that any observation with zero investment has to be dropped from the data. This typically leads to a large drop in sample size (that is not encountered with LP).

[19] It thus covers the following sectors: (i) mining and quarrying (C), (ii) manufacturing (D), (iii) electricity, gas and water supply (E), (iv) construction (F), v) wholesale and retail trade, repair of motor vehicles, motorcycles and personal and household goods (G), (vi) hotels and restaurants (H), (vii) transport, storage and communication (I), (viii) financial intermediation (J), and ix) real estate, renting and business activities (K).

[20] The SES is a stratified sample. The stratification criteria refer respectively to the region (NUTS-groups), the principal economic activity (NACE-groups) and the size of the firm. The sample size in each stratum depends on the size of the firm. Sampling percentages of firms are respectively equal to 10, 50 and 100 percent when the number of workers is lower than 50, between 50 and 99, and above 100. Within a firm, sampling percentages of employees also depend on size. Sampling percentages of employees reach respectively 100, 50, 25, 14.3 and 10 percent when the number of workers is lower than 20, between 20 and 50, between 50 and 99, between 100 and 199, and between 200 and 299. Firms employing 300 workers or more have to report information for an absolute number of employees. This number ranges between 30 (for firms with between 300 and 349 workers) and 200 (for firms with 12,000 workers or more). To guarantee that firms report information on a representative sample of their workers, they are asked to follow a specific procedure. First, they have to rank their employees in alphabetical order. Next, Statistics Belgium gives them a random letter (e.g. the letter O) from which they have to start when reporting information on their employees (following the alphabetical order of workers' names in their list). If they reach the letter Z and still have to provide information on some of their employees, they have to continue from the letter A in their list. Moreover, firms that employ different categories of workers, namely managers, blue- and/or white-collar workers, have to set up a separate alphabetical list for each of these categories and to report information on a number of workers in these different groups that is proportional to their share in the firm's total employment. For example, a firm with 300 employees (namely, 60 managers, 180 white-collar workers and 60 blue-collar workers) will have to report information on 30 workers (namely, 6 managers, 18 white-collar workers and 6 blue-collar workers). For more details see Demunter (2000).

Intermediation (NACE 67). The merger of the SES and SBS datasets has been carried out by Statistics Belgium using firms' social security numbers.

A first point to consider for the econometric specification is that information in the SES refers to the month of October in each year, while data in the SBS are measured over entire calendar years, that is, over all months from January to December of each year. Hence, to avoid running a regression where information on the dependent variable precedes (to a large extent) the date on which the explanatory variables have been recorded, all explanatory variables in Equations (1) and (2) have been lagged by one year. In this way, information on diversity indices relative to the month of October in year t is used to explain firm-level productivity and wages in year t+1. This methodological choice restricts our sample to firms that are observed in at least two consecutive years. It thus leads to the over-representation of medium-sized and large firms given that sampling percentages of firms in our data set increase with the size of the latter.[21] Next, we exclude workers and firms for which data are missing or inaccurate.[22] Finally, we drop firms with less than 10 observations, the reason for this being our use of the first and second moments of workers' characteristics at the firm level.[23]

Our final sample consists of an unbalanced panel of 7,463 firm-year-observations from 2,431 firms. It is representative of all medium-sized and large firms in the Belgian private sector, with the exception of large parts of the financial sector (NACE J) and the electricity, gas and water supply industry (NACE E).

[INSERT TABLE 1]

Table 1 sets out the means and standard deviations of selected variables. We observe that firms have a mean value added per hour worked of 61.06 EUR and that workers' mean gross hourly wage stands at 17.14 EUR. As regards diversity indicators, we find that the intra-firm standard deviation (the dissimilarity index) reaches respectively 9.33 (12.61) for age, 1.90 (2.54) for education, and 0.35 (0.46) for gender. Employees in our sample have on average 11.44 years of education, are 38.42 years old, and are essentially concentrated in the manufacturing industry (57%), wholesale and retail trade, repair of motor vehicles, motorcycles and personal and household goods (12%), construction (10%) and real estate, renting and business activities (11%). Moreover, firms

[21] See footnote 19.
[22] For instance, we eliminate a (very small) number of firms for which the recorded value added was negative.
[23] This restriction is unlikely to affect our results as it leads to a very small drop in sample size. The average number of observations per firm in each year is equal to 35 in our final sample.

employ on average 268 workers, 27 per cent of women, 45% of white-collar workers, 61% of workers with less than ten years of tenure, 4 per cent of workers with a fixed-term employment contract, and 2 per cent of part-time workers.

5. Empirical results

5.1. Benchmark specification

Given the above mentioned econometric issues associated with pooled OLS and FE estimations, we focus in this section on findings based on the GMM-SYS and LP estimators. Table 2 shows the impact of diversity indicators (the standard deviation and dissimilarity index, respectively) on productivity, mean wages and productivity-wage gaps at the firm-level.

[INSERT TABLE 2]

GMM-SYS estimates are reported in columns (1) to (6). To examine their reliability, we first apply the Hansen and Arellano-Bond tests. For all specifications, they respectively do not reject the null hypothesis of valid instruments[24] and of no second-order autocorrelation in the first differenced errors. Results in columns (1) and (2) show that age and gender diversity have a significant negative influence on productivity. More precisely, they suggest that if age diversity increases by one standard deviation (that is by respectively 1.82 and 2.52 years for the standard deviation and dissimilarity index), productivity on average decreases by 4 per cent.[25] The mean impact on productivity of a standard deviation increase in gender diversity (measured through the standard deviation or dissimilarity index) is also estimated at about -4%.[26] Concerning education diversity, we find that the regression coefficient is positive but statistically insignificant in both specifications.

LP estimates, reported in columns (7) and (8), confirm that age and gender diversity are harmful for productivity. Point estimates indeed suggest that an increase in these variables of one standard deviation hampers productivity on average by 1.3 and 1.7%, respectively. As regards the coefficient on educational diversity, it is still positive but it is now also significantly different from zero. More precisely, results suggest that when educational diversity increases by one standard deviation, productivity on average rises by approximately 2.7%.

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[24] First and second lags of explanatory variables (except time dummies) are used as instruments.
[25] -0.022*1.82 = -0.04 = -4% and -0.016*2.52 = -0.04 = -4%.
[26] -0.260*0.15 = -0.039 = -3.9% and -0.176*0.22 = -0.039 = -3.9%.

Findings in columns (3) and (4) show that GMM-SYS regression coefficients associated to diversity indices are of the same sign and order of magnitude in the wage and productivity equations. While age and gender diversity are found to depress mean workers' wages, the reverse finding is found for educational diversity. Results in columns (5) and (6) further indicate that educational and gender diversity have a non-significant impact on the productivity-wage gap. Gains (losses) due to educational (gender) diversity thus appear to be shared 'competitively' between workers and firms so that profits remain unaffected. In contrast, age diversity is found to have a stronger negative impact on productivity than on wages. More precisely, results show that an increase of one standard deviation in the age diversity index decreases the productivity-wage gap (i.e. profits) by about 2,3% on average.[27]

5.2 Does the technological/knowledge environment matter?

The diversity-productivity-wage nexus is likely to vary across working environments. Various theoretical arguments (reviewed in section 2.2) suggest in particular that the former may differ between high-tech/knowledge intensive sectors and more traditional industries. Given the scarcity of empirical evidence on this issue, in this section we present estimates of our model for two distinct types of firms: those belonging to high-medium tech/knowledge intensive sectors (HT/KIS) and those that do not. The subdivision of firms is based on a taxonomy developed by Eurostat (2012) that classifies manufacturing industries (at NACE 2- and/or 3-digit level) according to their degree of technological intensity (primarily assessed though the ratio of R&D expenditures to value added) and services (at NACE 2- digit level) according to their degree of knowledge intensity (i.e. the share of tertiary educated people in the activity).[28]

Applied to our sample, this Eurostat (2012) taxonomy classifies 679 firms as HT/KIS and 1,778 as non-HT/KIS firms.[29] As shown in Table 1, these two types of firms differ along several dimensions. Both the average hourly value added and wage are higher in HT/KIS compared to non-HT/KIS firms, confirming the intuition that HT/KIS firms are in general more productive. Moreover,

[27] Results presented in Table 3 remain quite stable when replacing the gender standard deviation/dissimilarity index by an alternative indicator, namely the share of women times the share of men within firms (see Appendix 1). We also tested for a non linear relationship between the dependent variables (productivity, wages and productivity-wage gaps) and diversity indices. Therefore, we respectively include diversity indices in level, squared (and cubed) and used dummy variables to test for structural breaks notably at the 33rd and 66th percentiles of the distribution of the diversity indices. Results, reported in Appendix 2, show no evidence of nonlinearities.

[28] For more details see Appendix 3.

[29] The sum of HT/KIS and non-HT/KIS firms (2,457) is greater than the total number of firms in the baseline model (2,431). This is due to a small number of firms that changed NACE codes during the period 1999-2006. Suppression of these firms does not affect our conclusions.

HT/KIS firms are found to have a significantly larger capital stock and to invest more. Differences in age, educational and occupational composition also exist: the workforce of HT/KIS firms is on average much more concentrated in white collar occupations (62 vs. 39%), somewhat more educated and slightly younger compared to non-HT/KIS firms. Interestingly, HT/KIS firms are also characterised by a more feminine labour force (33 vs. 27%). Both HT/KIS and non-HT/KIS employment is predominantly concentrated in the manufacturing sector (respectively around 53 and 58%). Yet, while almost 45% of HT/KIS employment is found in real estate, renting and business activities and financial intermediation, about a third of non-HT/KIS workers is employed in the construction and wholesale and retail trade industry (including repair of motor vehicles, motorcycles and personal and household goods).

To formally test for differences between HT/KIS and non-HT/KIS firms, we add to our benchmark specification: i) a dummy variable that equals 1 if the firm is classified as being HT/KIS, and ii) interactions between this HT/KIS dummy and first and second moments of age, education and gender variables.

[INSERT TABLE 3]

Results based on GMM-SYS and LP estimators are reported in Table 3. The reliability of GMM-SYS estimates is supported by the outcomes of the Hansen and Arellano-Bond tests. For all specifications, they respectively do not reject the null hypothesis of valid instruments[30] and of no second-order autocorrelation in first differenced errors.

Overall, GMM-SYS and LP estimates again show that age (educational) diversity is detrimental (beneficial) for firm productivity. Moreover, given that interaction effects with the HT/KIS dummy variable are systematically insignificant, it appears that the size of the elasticity between productivity and age/educational diversity does not depend on firms' technological/knowledge environment. Furthermore, results indicate that age and educational diversity have a similar impact on wages and productivity. On the whole, they thus suggest that profitability (i.e. the productivity-wage gap) does not depend on the diversity of the workforce in terms of education or age.

Results regarding the consequences of gender diversity on productivity are quite remarkable. Indeed, while gender diversity is still found to hamper firms' productivity in more traditional sectors,

[30] Yet, it should be acknowledged that Hansen over-identification tests for the firm-level wage regressions are only significant at the 5% level (p-values are respectively equal to 0.055 and 0.065). Therefore, results for wages should be interpreted with caution.

firms belonging to high-medium tech/knowledge intensive sectors appear to be significantly more productive when employing a more gender-balanced workforce. More precisely, estimates suggest that if gender diversity – measured respectively through the standard deviation and dissimilarity index – increases by one standard deviation, productivity increases (decreases) on average by between 2.5 and 6% (3 and 5%) in HT/KIS firms (non-HT-KIS firms). Besides, results show that gender diversity has no significant influence on the productivity-wage gap in both types of environments.

Robustness tests

To examine the robustness of these results, we used two alternative taxonomies enabling to distinguish between technological/knowledge intensive industries and more traditional sectors. These are respectively the KIA and ICT nomenclatures developed by Eurostat (2012) and O'Mahony and van Ark (2003). The former differs from the HT/KIS classification in that it applies the same methodology to all sectors of industries and services. Moreover, it focuses solely on the level of education of the labour force. More precisely, it classifies an industry as knowledge intensive if the share of tertiary educated workers represents more than one third of total employment in that industry. The ICT nomenclature classifies industries according to their ICT capital intensity at the NACE 3-digit level. It groups industries based on whether they produce ICT goods and services and whether they intensively use ICT or not.[31]

Results based on these alternative nomenclatures are shown in Appendices 5 and 6.[32] They are very similar to those obtained on the basis of the HT/KIS classification. This is quite remarkable, particularly given that correlation coefficients between HT/KIS, KIA and ICT taxonomies are not very high (see Appendix 4). Overall, results again highlight that productivity depends positively (negatively) on educational (age) diversity. Moreover, they show that gender diversity is detrimental (beneficial) for firm added value in traditional (knowledge/ICT intensive) industries. In line with our benchmark specification (see Table 3), results also indicate that age (educational) diversity has a negative (no significant) impact on firm profits. As regards the influence of gender diversity on the productivity-wage gap, results depend on whether we rely on the ICT or KIA nomenclatures. In the former case, profits do not depend on whether the labour force is gender balanced or not. In the

[31] For more details see Appendix 3.

[32] For the sake of brevity, we only report results based on the standard deviation of age, education and gender. Estimates using the dissimilarity index (available upon request) lead to similar conclusions.

latter, gender diversity is found to increase (decrease) profits in firms belonging to knowledge intensive (traditional) sectors.[33]

6. Conclusion and discussion

This paper estimates the impact of workforce diversity (in terms of education, age and gender) on productivity, wages and productivity-wage gaps (i.e. profits). It contributes significantly to the existing literature as it is one of the first: i) to rely on large representative data (i.e. Belgian linked employer-employee panel data covering most private sector firms over the period 1999-2006), ii) to address important methodological issues such as firm-level invariant heterogeneity and endogeneity, iii) to examine how the benefits or losses of labour diversity are shared between workers and firms (i.e. to extend the analysis to wages and productivity-wage gaps), and iv) to investigate whether the diversity-productivity-wage nexus depends on the degree of technological/knowledge intensity of firms.

Findings, based on the generalized method of moments (GMM) and Levinsohn and Petrin (2003) estimators, show that educational diversity is beneficial for firm productivity and wages. In contrast, age and gender diversity are found to hamper firm-level added value and average earnings. Yet, the consequences of gender diversity are found to depend on the technological/knowledge intensity of firms. While gender diversity generates significant gains in high-tech/knowledge intensive sectors, the reverse result is obtained in more traditional industries. Overall, findings do not point to sizeable productivity-wage gaps associated with educational and gender diversity. Age diversity, on the opposite, is generally found to decrease firm's profitability.

How can these findings be interpreted? Results from our benchmark specification showing that educational (age and gender) diversity improves (hamper) firm productivity are consistent with the theoretical predictions of Lazear (1999) and Jehn et al. (1999). The latter posit that diversity will only benefit productivity if the gains incurred by a more diverse workforce (due to complementary skills and information sets) outweigh additional communication costs and difficulties related to emotional conflicts. Moreover, they argue that this condition is unlikely to be satisfied for demographic diversity (heterogeneity in terms of e.g. age and gender) but may well be fulfilled for educational (i.e. task related) heterogeneity. In line with our results, they indeed suggest that mutual learning and collaboration among workers with different educational backgrounds may be sufficient to enhance efficiency.

[33] We also tested whether results vary according to firm size. Results, reported in Appendix 7, suggest that diversity variables have a similar impact on the productivity of smaller and bigger firms.

In contrast, our findings do not support Kremer's (1993) O-ring theory according to which profit-maximizing firms should match workers of similar skills/education together. They neither support social cognitive theory (Bandura, 1997) which suggests that gender diversity may be good for performance as it increases the heterogeneity of values, beliefs and attitudes of the members of a group, which in turn may stimulate critical thinking and prevent the escalation of commitment (i.e. inflated perception of group efficacy resulting in poor decision making). Results for gender and age diversity are more in line with the conclusions of the organizational literature (see e.g. Pfeffer, 1985), which emphasize the importance of social similarity (notably in terms of gender and age) to stimulate interaction, communication and cohesion among the workforce. On the opposite, findings relative to educational diversity are compatible with social comparison theory (Festinger, 1954). This theory highlights that workforce diversity may benefit the organization as it reduces rivalry and labour conflicts.

Interaction effects between gender diversity and the technological/knowledge environment of firms can be reconciled with the predictions of Prat (2002) and Jehn et al. (1999). The latter argue that the benefits of diversity are more likely to exceed the costs when the work environment is predominantly characterized by complex (rather than routine) tasks, negative complementarities (i.e. workers' actions are substitutes in the firm's payoff function) and innovative (rather than functional) output. Given that these features are more likely to be encountered in high-tech/knowledge intensive sectors than in more traditional industries, they may contribute to the explanation of our results.

Akerlof and Kranton (2000)'s model, introducing the concept of identity into an economic model of behavior, may also explain why productivity effects of gender diversity differ across environments with varying technological/knowledge intensity. The authors argue that gender diversity may negatively affect firm performance, especially if men constitute a socially 'dominant' group (Haile, 2012). Given that the workforce is less gender-balanced (see Table 1) and the environment potentially more 'macho' in traditional companies (e.g. construction) than in high-tech/knowledge intensive firms, their arguments appear to be in line with our results. Empirical findings are also consistent with the observation that high-tech/knowledge intensive sectors increasingly rely on inter-personal or 'soft' skills (that may be more effectively provided by women) and generally require less physical stamina than traditional firms, e.g. construction companies (Arun and Arun, 2002; Webster, 2007).

Overall, results regarding the impact of gender and educational diversity on the productivity-wage gap suggest that gains and losses associated with diversity are shared 'competitively' between workers and firms so that profits remain unaffected. In contrast, firm profitability is found to depend negatively on age diversity. According to Cataldi et al. (2012), older (younger) workers tend to be ‘over-paid’ (‘under-paid’) in Belgian private sector firms. Hence, the negative effect of age diversity on profitability is likely to derive from the fact that: i) increases in age diversity are essentially the consequence of an aging workforce, and ii) the ‘over-payment’ of older workers may outweigh the ‘underpayment’ of younger workers (as suggested by Cataldi et al., 2011).

Our results may have important implications for HRM. Diversity, in contrast to a widespread belief, may not always be beneficial for companies and workers. Moreover, consequences of diversity are found to substantially depend on the firm’s economic environment: firms in high-tech/knowledge intensive sectors are more likely to benefit from gender diversity than those in more traditional industries. Accordingly, the latter could learn from best practices implemented in the former to make gender diversity work. More generally, personnel measures aimed at improving the impact of age diversity on economic outcomes deserve special attention. Our estimates indeed highlight that the size of the effects associated with diversity (in terms of age, but also gender and education) is not negligible. Effective diversity management thus appears crucial for a firm’s success.

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Table 1: Descriptive statistics at the firm level (1999-2006)

	All firms		HT/KIS firms		Non-HT/KIS firms	
Variables	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Hourly wage (€[a])	17.14	5.39	18.38	5.68	16.64	5.18
Value-added per hour (€[a])	61.06	458.61	64.49	239.10	59.71	520.20
Average age (years)	38.42	4.19	37.45	4.35	38.80	4.07
Standard deviation of age	9.33	1.82	9.01	2.01	9.45	1.73
Age dissimilarity index	12.61	2.52	12.16	2.77	12.79	2.39
Average education (years)	11.44	1.76	12.32	1.79	11.09	1.62
Standard deviation of education	1.90	0.84	1.79	0.77	1.94	0.86
Education dissimilarity index	2.54	1.15	2.40	1.05	2.60	1.18
Women (%)	0.27	0.24	0.33	0.25	0.24	0.23
Standard deviation of gender	0.35	0.15	0.38	0.14	0.34	0.16
Gender dissimilarity index	0.46	0.22	0.51	0.20	0.45	0.22
Workers with tenure >= 10 years (%)	0.39	0.24	0.33	0.25	0.42	0.24
White-collar workers (%)	0.45	0.34	0.62	0.36	0.39	0.31
Part-time (< 30h/week, %)	0.02	0.07	0.02	0.06	0.02	0.07
Fixed-term employment contacts (%)	0.04	0.10	0.05	0.12	0.04	0.09
Sector (%)						
Mining and quarrying (C)	0.01	0.09	0.00	0.00	0.01	0.11
Manufacturing (D)	0.57	0.49	0.53	0.50	0.59	0.49
Electricity, gas and water supply (E)	0.00	0.06	0.00	0.00	0.01	0.07
Construction (F)	0.10	0.29	0.00	0.00	0.13	0.34
Wholesale and retail trade, repair of motor vehicles, motorcycles and personal and household goods (G)	0.12	0.33	0.00	0.00	0.17	0.37
Hotels and restaurant (H)	0.02	0.13	0.00	0.00	0.02	0.16
Transport, storage and communication (I)	0.06	0.24	0.05	0.21	0.07	0.25
Financial intermediation (J)	0.01	0.11	0.05	0.21	0.00	0.00
Real estate, renting and business activities (K)	0.11	0.31	0.38	0.49	0.00	0.01
Capital stock (€[a])	244,287	2,117,000	489,790	3,946,000	147,644	292,979
Investments (€[a])	18,543	254,447	40,205	476,648	10,019	24,221
Size of the firm (number of workers)	268.30	281.99	299.90	326.80	255.90	261.20
Number of observations	7463		2108		5355	
Number of firms [b]	2431		679		1778	

Notes: [a] At 2006 constant prices. [b] The sum of HT/KIS and non-HT/KIS firms exceeds the total number of firms due to a small number of them changing category during the observation period.

Table 2: Estimation results for the entire sample

	GMM-SYS						LP	
	Value added per hour worked (ln)		Mean wage per hour worked (ln)		Value added-wage gap (ln)		Value added per hour worked (ln)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Std. dev. age	-0.022***		-0.010***		-0.013*		-0.007**	
	(0.008)		(0.004)		(0.007)		(0.003)	
Age dissimilarity		-0.016***		-0.007***		-0.009*		-0.005*
		(0.006)		(0.003)		(0.005)		(0.003)
Std. dev. education	0.009		0.017**		-0.008		0.032***	
	(0.015)		(0.007)		(0.013)		(0.008)	
Education dissimilarity		0.007		0.012**		-0.005		0.024***
		(0.011)		(0.005)		(0.010)		(0.006)
Std. dev. gender	-0.260**		-0.140**		-0.120		-0.113*	
	(0.102)		(0.055)		(0.094)		(0.064)	
Gender dissimilarity		-0.176**		-0.097**		-0.079		-0.075*
		(0.076)		(0.041)		(0.069)		(0.039)
Average age	0.011***	0.011***	0.009***	0.009***	0.002	0.002	0.010***	0.010***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)
Average education	0.077***	0.077***	0.046***	0.046***	0.032***	0.032***	0.075***	0.075***
	(0.007)	(0.007)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.005)
Hansen over-identification test, *p*-value	0.765	0.767	0.152	0.172	0.487	0.480		
Arellano-Bond test for AR(2), *p*-value	0.123	0.124	0.370	0.356	0.560	0.561		
Number of observations	7463	7463	7463	7463	7463	7463	7461	7463
Number of firms	2431	2431	2431	2431	2431	2431	2431	2431

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors are reported between brackets. Regressions also control for: % workers with 10 years of tenure or more, % white-collar workers, % employees with a fixed-term contract, % part-time workers, firm size and capital stock, industries (8 dummies), and years dummies (7). AR(2) refers to second-order autocorrelation in first-differenced errors. GMM-SYS specifications include first and second lags of explanatory variables (except time dummies) as instruments.

Table 3: Estimation results for different technological/knowledge environments (HT/KIS nomenclature)

	GMM-SYS						LP	
	Value added per hour worked (ln)		Mean wage per hour worked (ln)		Value added-wage gap (ln)		Value added per hour worked (ln)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Std. dev. age	-0.022**		-0.011**		-0.011		-0.001	
	(0.010)		(0.005)		(0.009)		(0.005)	
Age dissimilarity		-0.017**		-0.007**		-0.009		-0.001
		(0.007)		(0.003)		(0.007)		(0.003)
Std. dev. education	0.011		0.001		0.010		0.025***	
	(0.022)		(0.010)		(0.021)		(0.009)	
Education dissimilarity		0.006		0.001		0.019***		0.019***
		(0.016)		(0.007)		(0.007)		(0.007)
Std. dev. gender	-0.327**		-0.172**		-0.155		-0.194***	
	(0.136)		(0.068)		(0.123)		(0.069)	
Gender dissimilarity		-0.230**		-0.119**		-0.112		-0.142***
		(0.100)		(0.050)		(0.089)		(0.039)
Std. dev. age*HT/KIS	0.011		0.006		0.005		-0.014	
	(0.026)		(0.012)		(0.024)		(0.009)	
Age dissimilarity*HT/KIS		0.011		0.004		0.007		-0.010
		(0.019)		(0.009)		(0.017)		(0.007)
Std. dev. education*HT/KIS	-0.007		0.039*		-0.047		0.033	
	(0.056)		(0.022)		(0.049)		(0.024)	
Education dissimilarity*HT/KIS		-0.001		0.026		-0.028		0.023
		(0.040)		(0.016)		(0.034)		(0.017)
Std. dev. gender*HT/KIS	0.716*		0.174		0.542		0.343**	
	(0.398)		(0.139)		(0.361)		(0.147)	
Gender dissimilarity*HT/KIS		0.527*		0.121		0.406		0.261***
		(0.283)		(0.102)		(0.255)		(0.091)
Average age	-0.005	-0.003	0.003	0.003	-0.008	-0.006	0.008***	0.008***
	(0.016)	(0.016)	(0.008)	(0.008)	(0.014)	(0.014)	(0.003)	(0.003)
Average education	0.055	0.048	0.002	0.002	0.053	0.046	0.063***	0.064***
	(0.043)	(0.042)	(0.020)	(0.019)	(0.040)	(0.039)	(0.005)	(0.007)
Average age*HT/KIS	0.035*	0.034	-0.001	-0.000	0.036**	0.034*	0.006	0.006
	(0.021)	(0.021)	(0.010)	(0.010)	(0.018)	(0.018)	(0.004)	(0.004)
Average education*HT/KIS	0.066	0.073	0.064**	0.062**	0.002	0.011	0.037***	0.037***

	(0.064)	(0.064)	(0.029)	(0.029)	(0.053)	(0.052)	(0.010)	(0.013)
HT/KIS	-2.552***	-2.635***	-0.934**	-0.896**	-1.618*	-1.739**	-0.691***	-0.689***
	(0.981)	(0.972)	(0.453)	(0.452)	(0.868)	(0.860)	(0.213)	(0.212)
Hansen over-identification test, *p*-value	0.177	0.192	0.055	0.065	0.334	0.306		
Arellano-Bond test for AR(2), *p*-value	0.117	0.116	0.458	0.442	0.499	0.502		
Number of observations	7463	7463	7463	7463	7463	7463	7461	7463
Number of firms	2431	2431	2431	2431	2431	2431	2431	2431

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported between brackets. Regressions also control for: % workers with 10 years of tenure or more, % white-collar workers, % employees with a fixed-term contract, % part-time workers, firm size and capital stock, industries (8 dummies), and years dummies (7). AR(2) refers to second-order autocorrelation in first-differenced errors. GMM-SYS specifications include first and second lags of explanatory variables (except time dummies) as instruments. HT/KIS = 1 if the firm belongs to a high-medium tech/knowledge intensive sector, according to the taxonomy developed by Eurostat (2012).

Appendix 1: Estimates for the entire sample using 'the share of women times the share of men' as gender diversity index

	GMM-SYS						LP	
	Value added per hour worked (ln)		Mean wage per hour worked (ln)		Value added-wage gap (ln)		Value added per hour worked (ln)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Std. dev. age	-0.022***		-0.009***		-0.013*		-0.007	
	(0.008)		(0.004)		(0.007)		(0.005)	
Age dissimilarity		-0.016***		-0.007***		-0.009*		-0.005*
		(0.006)		(0.003)		(0.005)		(0.003)
Std. dev. education	0.008		0.016**		-0.008		0.031***	
	(0.015)		(0.007)		(0.013)		(0.010)	
Education dissimilarity		0.006		0.012**		-0.005		0.023***
		(0.011)		(0.005)		(0.010)		(0.006)
Share of women * share of men	-0.390*	-0.389*	-0.234**	-0.230**	-0.156	-0.159	-0.160	-0.162*
	(0.229)	(0.229)	(0.115)	(0.116)	(0.197)	(0.197)	(0.109)	(0.090)
Average age	0.011***	0.011***	0.009***	0.009***	0.002	0.002	0.010***	0.010***
	(0.004)	(0.004)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)
Average education	0.077***	0.077***	0.046***	0.046***	0.031***	0.031***	0.075***	0.075***
	(0.007)	(0.007)	(0.003)	(0.003)	(0.006)	(0.006)	(0.007)	(0.007)
Hansen over-identification test, *p*-value	0.866	0.840	0.117	0.140	0.468	0.461		
Arellano-Bond test for AR(2), *p*-value	0.131	0.130	0.349	0.343	0.564	0.564		
Number of observations	7463	7463	7463	7463	7463	7463	7461	7463
Number of firms	2431	2431	2431	2431	2431	2431	2431	2431

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported between brackets. Regressions also control for: % workers with 10 years of tenure or more, % white-collar workers, % employees with a fixed-term contract, % part-time workers, firm size and capital stock, industries (8 dummies), and years dummies (7). AR(2) refers to second-order autocorrelation in first-differenced errors. GMM-SYS specifications include first and second lags of explanatory variables (except time dummies) as instruments.

Appendix 2: Estimation results including nonlinearities

	Testing for nonlinearities at the **33rd percentile**				Testing for nonlinearities at the **66th percentile**				Testing for nonlinearities at **33rd and 66th percentiles**			
	GMM-SYS			**LP**	**GMM-SYS**			**LP**	**GMM-SYS**			**LP**
	Value-added	Wage	Gap	Value-added	Value-added	Wage	Gap	Value-added	Value-added	Wage	Gap	Value-added
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Std. dev. age	-0.022*	-0.005	-0.017	-0.006	-0.023**	-0.009*	-0.014	-0.003	-0.046***	-0.009	-0.037**	-0.006
	(0.013)	(0.006)	(0.011)	(0.004)	(0.011)	(0.005)	(0.010)	(0.006)	(0.017)	(0.007)	(0.015)	(0.007)
Std. dev. education	0.032	0.003	0.028	0.035***	-0.010	0.013	-0.023	0.042***	-0.035	-0.010	-0.024	0.038*
	(0.020)	(0.010)	(0.018)	(0.008)	(0.016)	(0.009)	(0.015)	(0.012)	(0.031)	(0.014)	(0.030)	(0.020)
Std. dev. gender	-0.233**	-0.145**	-0.088	-0.082	-0.278***	-0.180***	-0.098	-0.178***	-0.387***	-0.203***	-0.185	-0.133
	(0.109)	(0.060)	(0.101)	(0.058)	(0.099)	(0.057)	(0.091)	(0.062)	(0.123)	(0.068)	(0.113)	(0.084)
Std. dev. age*p33	0.001	-0.002	0.003	0.001					0.010***	-0.001	0.010***	0.001
	(0.003)	(0.001)	(0.002)	(0.001)					(0.003)	(0.002)	(0.003)	(0.002)
Std. dev. education*p33	-0.012	0.011*	-0.022**	0.005					0.017	0.015*	0.001	0.003
	(0.012)	(0.006)	(0.010)	(0.007)					(0.021)	(0.009)	(0.020)	(0.014)
Std. dev. gender*p33	0.004	-0.012	0.016	-0.076*					0.147*	0.014	0.132**	-0.040
	(0.060)	(0.034)	(0.052)	(0.039)					(0.075)	(0.041)	(0.066)	(0.056)
Std. dev. age*p66					0.001	-0.001	0.001	-0.001	0.012**	-0.001	0.013***	0.000
					(0.002)	(0.001)	(0.002)	(0.001)	(0.005)	(0.002)	(0.005)	(0.003)
Std. dev. education*p66					0.015	0.006	0.009	-0.005	0.033	0.023**	0.010	-0.002
					(0.009)	(0.005)	(0.009)	(0.008)	(0.025)	(0.011)	(0.023)	(0.014)
Std. dev. gender*p66					0.018	0.034	-0.016	0.080*	0.163	0.057	0.106	0.044
					(0.066)	(0.031)	(0.055)	(0.045)	(0.105)	(0.052)	(0.088)	(0.069)
Average age	0.011***	0.009***	0.002	0.011***	0.011***	0.009***	0.001	0.011***	0.011***	0.010***	0.002	0.011***
	(0.003)	(0.001)	(0.003)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)
Average education	0.078***	0.047***	0.031***	0.079***	0.079***	0.047***	0.032***	0.079***	0.080***	0.048***	0.032***	0.079***
	(0.007)	(0.004)	(0.006)	(0.006)	(0.008)	(0.003)	(0.006)	(0.007)	(0.007)	(0.004)	(0.006)	(0.006)
Hansen test, *p*-value	0.735	0.069	0.809		0.669	0.339	0.413		0.711	0.176	0.685	
AR(2) test, *p*-value	0.125	0.339	0.588		0.123	0.355	0.565		0.107	0.374	0.595	
Number of observations	7463	7463	7463	7463	7463	7463	7463	7463	7463	7463	7463	7463
Number of firms	2431	2431	2431	2431	2431	2431	2431	2431	2431	2431	2431	2431

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported between brackets. Regressions also control for: % workers with 10 years of tenure or more, % white-collar workers, % employees with a fixed-term contract, % part-time workers, firm size and capital stock, industries (8 dummies), and years dummies (7). AR(2) refers to second-order autocorrelation in first-differenced errors. GMM-SYS specifications include first and second lags of explanatory variables (except time dummies) as instruments. HT/KIS = 1 if the firm belongs to a high-medium tech/knowledge intensive sector, according to the taxonomy developed by Eurostat (2012). p3 (p66) is a dummy variable that takes the value one if the variable is greater than the 33rd percentile (66th percentile). When p33 and p66 are included simultaneously, p33 takes the value one if the variable is greater than the 33rd percentile and smaller than the 66th percentile. The dependent variables are respectively: i) the value-added (i.e. the value added per hour worked (ln)), ii) the wage (i.e. the mean wage per hour worked (ln)), and iii) the gap (i.e. value added-wage gap (ln)).

Appendix 3: Description of HT/KIS, KIA and ICT taxonomies

a) High-medium tech/knowledge intensive sectors (HT/KIS - Eurostat, 2012)

Taxonomy that classifies manufacturing industries (at NACE 2- and/or 3-digit level) according to their degree of technological intensity (primarily assessed though the ratio of R&D expenditures to value added) and services (at NACE 2- digit level) according to their degree of knowledge intensity (i.e. the share of tertiary educated people in the activity)

HT/KIS firms are found in the following sectors: Aerospace (NACE 353); Computers, office machinery (NACE 30); Electronics-communications (NACE 32); Pharmaceuticals (NACE 244); Scientific instruments (NACE 33); Motor vehicles (NACE 34); Electrical machinery (NACE 31); Chemicals (NACE 24); Other transport equipment (NACE 352+354+355); Non-electrical machinery (NACE 29); Water transport (NACE 61); Air transport (NACE 62); Post and telecommunications (NACE 64); Financial intermediation, except insurance and pension funding (NACE 65); Insurance and pension funding, except compulsory social security (NACE 66); Activities auxiliary to financial intermediation (NACE 67); Real estate activities (NACE 70); Renting of machinery and equipment without operator and of personal and household goods (NACE 71); Computer and related activities (NACE 72); Research and development (NACE 73); Other business activities (NACE 74); Education (NACE 80); Health and social work (NACE 85); Recreational, cultural and sporting activities (NACE 92).

Non-HT/KIS firms are found in the following sectors: Rubber and plastic products (NACE 25); Shipbuilding (NACE 351); Other manufacturing (NACE 362 through 366); Non-ferrous metals (NACE 274+2753/54); Non-metallic mineral products (NACE 26); Fabricated metal products (NACE 28); Petroleum refining (NACE 23); Ferrous metals (NACE 271 through 273+2751/52); Paper printing (NACE 21+22); Textile and clothing (NACE 17 through 19); Food, beverages, and tobacco (NACE 15+16); Wood and furniture 20+361); Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel (NACE 50); Wholesale trade and commission trade, except of motor vehicles and motorcycles (NACE 51); Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods (NACE 52); Hotels and restaurants (NACE 55); Land transport; transport via pipelines (NACE 60); Supporting and auxiliary transport activities; activities of travel agencies (NACE63); Public administration and defense; compulsory social security (NACE 75); Sewage and refuse disposal, sanitation and similar activities (NACE 90); Activities of membership organization n.e.c. (NACE 91); Other service activities (NACE 93); Private households with employed persons (NACE 95); Extra-territorial organizations and bodies (NACE 99).

b) Knowledge intensive activities (KIA - Eurostat, 2012)

Taxonomy that classifies industries (both manufacturing and services) according to their degree of knowledge intensity (assessed through the share of tertiary educated people at the NACE 2-digit level). An industry is classified as knowledge intensive if tertiary educated persons employed (according ISCED'97, levels 5+6) represent more than 33% of the total employment in that industry.

KIA firms are found in the following sectors: Manufacture of coke, refined petroleum products and nuclear fuel (NACE 23); Manufacture of chemicals and chemical products (NACE 24); Manufacture of office machinery and computers (NACE 30); Manufacture of radio, television and communication equipment and apparatus (NACE 32); Manufacture of medical, precision and optical instruments, watches and clocks (NACE 33); Air transport

(NACE 62); Financial intermediation, except insurance and pension funding (NACE 65); Insurance and pension funding, except compulsory social security (NACE 66); Activities auxiliary to financial intermediation (NACE 67); Computer and related activities (NACE 72); Research and development (NACE 73); Other business activities (NACE 74); Public administration and defence; compulsory social security (NACE75); Education (NACE 80); Health and social work (NACE 85); Activities of membership organizations n.e.c. (NACE 91), Recreational, cultural and sporting activities (NACE 92); Extra-territorial organizations and bodies (NACE 99).

c) Information and communication technology industries (ICT – O'Mahony and van Ark, 2003)

Taxonomy that classifies industries according to their ICT capital intensity at the NACE 3-digit level. It groups industries based on whether they produce ICT goods and services and whether they intensively use ICT or not.

ICT firms are found in the following sectors: Clothing (NACE 18); Printing and publishing (NACE 22); Mechanical engineering (NACE 29); Other electrical machinery and apparatus, except insulated wire (NACE 31); Other instruments, except scientific instruments (NACE 33); Building and repairing of ships and boats (NACE 351); Aircraft and spacecraft (NACE 353); Furniture, miscellaneous manufacturing; recycling (NACE 36-37); Wholesale trade and commission trade, except of motor vehicles and motorcycles (NACE 51); Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods (NACE 52); Financial activities, except insurance and pension funding (NACE 65); Activities auxiliary to financial intermediation (NACE 67); Renting of machinery and equipment (NACE 71); Legal, technical and advertising (NACE 741-743); Office machinery (NACE 30); Insulated wire (NACE 313); Electronic valves and tubes (NACE 321); Telecommunication equipment (NACE 322); Radio and television receivers (NACE 323); Scientific instruments (NACE 331); Communications (NACE 64); Computer and related activities (NACE 72).

Non-ICT firms are found in the following sectors: Quarrying (NACE 14); Food, drink and tobacco (NACE 15-16); Textiles (NACE 17); Leather and footwear (NACE 19); Wood and products of wood and cork (NACE 20); Pulp, paper and paper products (NACE 21); Mineral oil refining, coke and nuclear fuel (NACE 23); Chemicals (NACE 24); Rubbers and plastics (NACE 25); Non-metallic mineral products (NACE 26); Basic metals (NACE 27); Fabricated metal products (NACE 28); Motor vehicles (NACE 34); Construction (NACE 45); Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel (NACE 50); Hotels and restaurants (NACE 55); Inland transport (NACE 60); Water transport (NACE 61); Air transport (NACE 62); Supporting and auxiliary transport activities; activities of travel agencies (NACE 63); Real estate activities (NACE 70); Other business activities (NACE 749).

Appendix 4: Correlation coefficients between HT/KIS, KIA and ICT taxonomies

	HT/KIS	KIA	ICT
HT/KIS	1		
KIA	0.59	1	
ICT	0.49	0.22	1

Appendix 5: Estimates using the KIA taxonomy

	GMM-SYS Value added per hour worked (ln)	GMM-SYS Mean wage per hour worked (ln)	GMM-SYS Value added-wage gap (ln)	LP Value added-wage gap (ln)
	(1)	(2)	(3)	(4)
Std. dev. age	-0.020**	-0.004	-0.016**	-0.005
	(0.008)	(0.004)	(0.007)	(0.004)
Std. dev. education	0.017	0.013*	0.005	0.024***
	(0.015)	(0.007)	(0.014)	(0.009)
Std. dev. gender	-0.329***	-0.080	-0.249**	-0.137**
	(0.107)	(0.055)	(0.103)	(0.069)
Std. dev. age *KIA	-0.000	-0.018*	0.018	-0.005
	(0.027)	(0.010)	(0.023)	(0.012)
Std. dev. education*KIA	-0.021	0.017	-0.038	0.039
	(0.042)	(0.020)	(0.034)	(0.024)
Std. dev. gender*KIA	0.696**	0.025	0.671**	0.133
	(0.330)	(0.140)	(0.288)	(0.148)
Average age	0.002	0.008***	-0.006*	0.004*
	(0.003)	(0.001)	(0.003)	(0.002)
Average education	0.063***	0.031***	0.031***	0.059***
	(0.008)	(0.004)	(0.007)	(0.006)
Average age *KIA	0.031***	0.007**	0.024***	0.024***
	(0.008)	(0.003)	(0.007)	(0.005)
Average education*KIA	0.037**	0.038***	-0.001	0.051***
	(0.014)	(0.007)	(0.012)	(0.010)
KIA	-1.605***	-0.448***	-1.156***	-1.459***
	(0.340)	(0.159)	(0.301)	(0.211)
Hansen over-identification test, *p*-value	0.639	0.001	0.674	
Arellano-Bond test for AR(2), *p*-value	0.161	0.375	0.590	
Number of observations	7463	7463	7463	7463
Number of firms	2431	2431	2431	2431

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported between brackets. Regressions also control for: % workers with 10 years of tenure or more, % white-collar workers, % employees with a fixed-term contract, % part-time workers, firm size and capital stock, industries (8 dummies), and years dummies (7). AR(2) refers to second-order autocorrelation in first-differenced errors. GMM-SYS specifications include first and second lags of explanatory variables (except time dummies) as instruments. KIA = 1 if the firm belongs to a knowledge intensive industry, according to the taxonomy developed by Eurostat (2012).

Appendix 6: Estimates using the ICT taxonomy

	GMM-SYS Value added per hour worked (ln)	GMM-SYS Mean wage per hour worked (ln)	GMM-SYS Value added-wage gap (ln)	LP Value added-wage gap (ln)
	(1)	(2)	(3)	(4)
Std. dev. age	-0.039***	-0.013***	-0.026***	-0.003
	(0.011)	(0.005)	(0.009)	(0.006)
Std. dev. education	0.008	0.017**	-0.008	0.033***
	(0.016)	(0.008)	(0.015)	(0.010)
Std. dev. gender	-0.362***	-0.186***	-0.176	-0.208***
	(0.124)	(0.065)	(0.114)	(0.069)
Std. dev. age *ICT	0.051**	0.012	0.040**	-0.005
	(0.024)	(0.011)	(0.020)	(0.008)
Std. dev. education*ICT	0.017	0.008	0.009	0.000
	(0.037)	(0.018)	(0.032)	(0.019)
Std. dev. gender*ICT	0.533**	0.237*	0.295	0.366***
	(0.265)	(0.138)	(0.233)	(0.118)
Average age	0.019***	0.010***	0.009***	0.010***
	(0.004)	(0.002)	(0.003)	(0.003)
Average education	0.067***	0.036***	0.031***	0.060***
	(0.008)	(0.004)	(0.007)	(0.006)
Average age *ICT	-0.025***	-0.002	-0.023***	-0.002
	(0.007)	(0.003)	(0.005)	(0.004)
Average education*ICT	0.036**	0.032***	0.004	0.042***
	(0.015)	(0.007)	(0.012)	(0.012)
ICT	-0.184	-0.481***	0.297	-0.482**
	(0.313)	(0.149)	(0.269)	(0.226)
Hansen over-identification test, *p*-value	0.553	0.088	0.183	
Arellano-Bond test for AR(2), *p*-value	0.063	0.336	0.509	
Number of observations	7463	7463	7463	7463
Number of firms	2431	2431	2431	2431

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported between brackets. Regressions also control for: % workers with 10 years of tenure or more, % white-collar workers, % employees with a fixed-term contract, % part-time workers, firm size and capital stock, industries (8 dummies), and years dummies (7). AR(2) refers to second-order autocorrelation in first-differenced errors. GMM-SYS specifications include first and second lags of explanatory variables (except time dummies) as instruments. ICT = 1 if the firm belongs to a sector using or producing intensively ICT (information and communication technology) goods and services, according to the taxonomy developed by O'Mahony and van Ark (2003)

Appendix 7: Estimation results including interaction effects with firm size

	Interactions with **firm size < 75 workers**				Interactions with **firm size < 100 workers**				Interactions with **firm size < 125 workers**			
	GMM-SYS			**LP**	**GMM-SYS**			**LP**	**GMM-SYS**			**LP**
	Value-added	Wage	Gap	Value-added	Value-added	Wage	Gap	Value-added	Value-added	Wage	Gap	Value-added
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Std. dev. age	-0.027***	-0.014***	-0.013*	-0.004	-0.027***	-0.015***	-0.012	-0.004	-0.028***	-0.015***	-0.012	-0.004
	(0.009)	(0.005)	(0.008)	(0.006)	(0.009)	(0.005)	(0.008)	(0.005)	(0.009)	(0.005)	(0.008)	(0.005)
Std. dev. education	0.011	0.022***	-0.011	0.034***	0.011	0.021***	-0.011	0.034***	0.011	0.021***	-0.010	0.034***
	(0.016)	(0.008)	(0.014)	(0.011)	(0.016)	(0.008)	(0.014)	(0.011)	(0.016)	(0.008)	(0.014)	(0.011)
Std. dev. gender	-0.255**	-0.161***	-0.094	-0.140**	-0.261**	-0.171***	-0.089	-0.147**	-0.259**	-0.172***	-0.086	-0.147**
	(0.110)	(0.062)	(0.103)	(0.065)	(0.110)	(0.062)	(0.103)	(0.066)	(0.110)	(0.062)	(0.103)	(0.066)
Std. dev. age*SME	0.033	0.018	0.015	-0.005	0.033	0.025*	0.008	-0.004	0.040	0.028*	0.011	-0.004
	(0.033)	(0.016)	(0.030)	(0.007)	(0.031)	(0.015)	(0.029)	(0.007)	(0.031)	(0.015)	(0.028)	(0.007)
Std. dev. education*SME	-0.004	-0.025	0.021	-0.004	0.002	-0.012	0.014	-0.005	0.006	-0.006	0.012	-0.005
	(0.033)	(0.016)	(0.031)	(0.018)	(0.032)	(0.016)	(0.030)	(0.015)	(0.032)	(0.015)	(0.030)	(0.015)
Std. dev. gender*SME	0.144	0.291*	-0.147	0.078	0.230	0.380**	-0.151	0.097	0.213	0.357**	-0.144	0.097
	(0.301)	(0.156)	(0.264)	(0.103)	(0.298)	(0.154)	(0.263)	(0.087)	(0.313)	(0.156)	(0.270)	(0.087)
Average age	0.011***	0.010***	0.001	0.010***	0.011***	0.010***	0.001	0.010***	0.011***	0.010***	0.001	0.010***
	(0.004)	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)
Average education	0.081***	0.050***	0.031***	0.082***	0.082***	0.050***	0.031***	0.083***	0.082***	0.050***	0.031***	0.083***
	(0.008)	(0.004)	(0.006)	(0.007)	(0.008)	(0.004)	(0.006)	(0.008)	(0.008)	(0.004)	(0.006)	(0.008)
Average age*SME	-0.000	-0.003	0.003	0.002	-0.001	-0.005*	0.004	0.002	-0.000	-0.005*	0.004	0.002
	(0.007)	(0.003)	(0.007)	(0.004)	(0.006)	(0.003)	(0.007)	(0.004)	(0.006)	(0.003)	(0.006)	(0.004)
Average education*SME	-0.030**	-0.030***	0.000	-0.016	-0.033***	-0.030***	-0.002	-0.018**	-0.028**	-0.028***	0.000	-0.017
	(0.012)	(0.006)	(0.011)	(0.011)	(0.012)	(0.006)	(0.011)	(0.009)	(0.012)	(0.006)	(0.011)	(0.011)
SME	-0.030	0.186	-0.217	0.090	-0.029	0.148	-0.177	0.100	-0.138	0.089	-0.228	0.086
	(0.286)	(0.143)	(0.237)	(0.240)	(0.278)	(0.139)	(0.231)	(0.190)	(0.281)	(0.138)	(0.230)	(0.215)
Hansen test, *p*-value	0.634	0.301	0.370		0.668	0.234	0.398		0.708	0.127	0.388	
AR(2) test, *p*-value	0.114	0.419	0.556		0.115	0.399	0.563		0.118	0.354	0.549	
Number of observations	7463	7463	7463	7463	7463	7463	7463	7463	7463	7463	7463	7463
Number of firms	2431	2431	2431	2431	2431	2431	2431	2431	2431	2431	2431	2431

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are reported between brackets. Regressions also control for : % workers with 10 years of tenure or more, % white-collar workers, % employees with a fixed-term contract, % part-time workers, firm size and capital stock, industries (8 dummies), and years dummies (7). AR(2) refers to second-order autocorrelation in first-differenced errors. GMM-SYS specifications include first and second lags of explanatory variables (except time dummies) as instruments. HT/KIS = 1 if the firm belongs to a high-medium tech/knowledge intensive sector, according to the taxonomy developed by Eurostat (2012). SME is a dummy variable that takes the value one respectively when firm size is lower than 75, 100 and 125 workers. The dependent variables are respectively: i) the value-added (i.e. the value added per hour worked (ln)), ii) the wage (i.e. the mean wage per hour worked (ln)), and iii) the gap (i.e. value added-wage gap (ln)).