The heterogeneous effects of workplace diversity on wages and productivity*

Andrea Garnero§

ENS, Paris School of Economics and SBS-EM (DULBEA)

François Rycx

Université Libre de Bruxelles, SBS-EM (CEB, DULBEA) and IZA

6/09/2012

PRELIMINARY VERSION

Abstract

Using detailed matched employer-employee panel data for Belgium over the period 1999-2006, we investigate the impact of workforce diversity on productivity and wages. Findings using GMM and the Levinsohn-Petrin approach suggest that workforce diversity has heterogeneous effects on productivity and wages at firm level: demographic diversity (i.e. age and gender) has a negative impact on productivity and wages while education diversity has a positive one. Moreover, we find that the effect of diversity differs according to the firm environment: in high-tech/knowledge intensive sectors also gender diversity has a positive effect on productivity. Results do not point to any sizeable productivity-wage gap: the benefits or losses of diversity are evenly shared between firms and workers. The findings are robust to different variables, specifications and estimation methods.

Keywords: workforce diversity; productivity; wages; linked panel data.

JEL codes: D24, J24, J31, M12

---

* We would like to thank Statistics Belgium for giving access to the data. We are grateful to Philippe Askenazy, Pekka Ilmakunnas, Sile O'Dorchai and to audiences in Brussels and Paris for helpful comments and discussions. The usual disclaimer applies.

§ Corresponding author. Address: Université Libre de Bruxelles, Avenue F.D. Roosevelt, 50 - CP-140, B-1050 Brussels – Belgium, Phone: +32 2 650 4124, e-mail: agarnero@pse.ens.fr.

1. Introduction

Managing human resources in a firm is a key issue for the success of an entrepreneur. This does not simply consist in dealing with institutional settings and bureaucratic procedures nor in treating single workers' necessities. Firms often need different types of workers in terms of tasks to be accomplished and hence different workers in terms of education, physical stamina or reactivity. However, diversity can also lead to misunderstandings and personal conflicts which would harm productivity and profits. Managing properly the workforce of a firm means also (and perhaps mostly) managing its composition and complementarities in order to foster productivity, well-being and, as a result, firm's success. Moreover, diversity can have different effects according to the work environment. Common sense would suggest that some traditional industries (e.g. construction) might require a more homogenous workforce while in more innovative ones diversity might be beneficial for creative thinking and innovation. So, what is the right workforce mix to enhance productivity at firm level? And how are the possible benefits and losses distributed across firms and employees? And finally, does the work environment matter?

Workforce diversity[1] has become an essential business concern. More and more firms have a "diversity manager" in charge of not only promoting but really managing diversity among the workforce. Firms, but also public administrations, have to face these challenges and manage diversity internally, among management and staff, and externally in their environments (customers, suppliers, contractors etc.). In fact, workforce diversity is also considered as a tool of corporate social responsibility, marketing and social communication strategy, but also as a resource imperative given the changing demographics in the workforce. Today's labour force is getting more and more heterogeneous: ageing, migration, women empowerment and technological change are key drivers of this phenomenon. Moreover, in many countries companies are under legislative pressure to diversify the workforce either through quotas or affirmative action.[2] Diversity is therefore both a challenge and an opportunity for firms which can benefit from a more diverse workforce but also entail some costs. Workers could benefit (or lose) from more diverse colleagues not only in terms of a more (or less) enjoyable working environment, but also in economics terms. In fact, if workforce diversity increases (or decreases) productivity of a firm, in a perfect competitive framework this should reflect in higher (or lower) wages for workers. Moreover, the relationship between workforce diversity and productivity is likely to differ across firms: certain characteristics of the work environment such as computerization or the use of innovative technologies can interact differently with workforce composition. In high-tech/knowledge intensive sectors the job requirements in terms of skills ("hard" and "soft" such as interpersonal skills, team-working, etc.), physical stamina or creative thinking are very different and therefore firms in high-

[1] In human resource management (HRM), the term "workforce diversity" 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. They usually refer to dimensions such as gender, age, sexual orientation, religion, ethnicity, social origins and physical appearance.

[2] At the beginning, especially in the USA, diversity was still closely linked to the fight against discrimination and hence with "affirmative action". There seems now to be a movement toward a more systematic, positive, organizational approach of diversity management.

tech/knowledge intensive intensive industries might benefit more from diversity than traditional industries.

In light of this evolution, an accurate understanding of the impact of workforce diversity on firm productivity and on the share of the gains and losses and on the role of the ICT environment has emerged as an increasingly important issue. In economic theory the simple question of diversity and performance goes back to Adam Smith who in the *Wealth of Nations* (1776) states that worker heterogeneity benefits firm production. More recently Becker (1957) and Lazear (1999) have formalized the relationship between diversity and firm performance by pointing out the presence of communication problems driven by demographic diversity while education/skills diversity yields positive effects thanks to complementarities. The empirical literature is neither rich[3] nor very conclusive. Moreover, most of the previous studies should be considered with caution due to methodological and/or data limitations. In addition, the literature on the impact of diversity on wages is practically non-existent (there is only one paper to our knowledge looking at wages on top of productivity).

This paper aims to fill these gaps by developing a microeconometric approach to test the impact of workforce diversity in terms of age, education and gender on productivity and wages. More precisely, we start by examining how workforce diversity in terms of age, education and gender affects productivity of firms and wages and we test for the presence of productivity-wage gaps. To do so, we use a detailed linked employer-employee panel dataset of Belgian firms and workers which allows studying the impact of worker diversity both from the firm and worker perspective and different econometrics techniques (OLS and GMM but also a more structural approach developed by Levinsohn and Petrin, 2003). Secondly, we test our results differentiating across sectors according to the technological environment. The results show that, consistently with the theory, in traditional industries age and gender diversity have a negative effect on productivity and wages and education tends to have a positive effect on both, while in high-tech/knowledge intensive industries education and gender diversity are a positive factor. Estimates find no significant productivity-wage gap.

The present paper contributes to the existing literature in several ways. First, it provides empirical evidence regarding (i) the impact of different dimensions of diversity (age, gender and education) on productivity and (ii) the sharing of the benefits and the costs of diversity between firms and workers. Second, the paper differentiates the impact of workforce diversity between sectors. Third, our access to a large employer-employee panel data set allows us to estimate different models controlling for a wide range of worker and firm characteristics. Finally, our estimates address several econometric issues such as the potential endogeneity of workforce diversity or the existence of unobserved firm characteristics or unobserved productivity shocks.

The layout of the rest of the paper is as follows. Section 2 summarizes previous results in the literature. Section 3 presents the estimation strategy and section 4 describes the dataset and

[3] Analysis of diversity has a long tradition in human resource management (HRM) research. In economics, despite the growing interest for personnel economics, the literature so far focuses only on incentives, pay structures, work organization (diversity issues are not treated in the summa on HRM and productivity by Bloom and Van Reenen, 2011).

presents summary statistics. Regression results and robustness tests for the baseline model are discussed in Section 5.1 and the impact of the technological environment in Section 5.2. Section 6 concludes.

2. Literature

There are several ways to model the effect of workforce diversity on productivity: Alesina and La Ferrara (2005) refer to three main strands: models based on *preferences* (individuals may attribute positive utility to the well-being of members of their own group, and negative utility to that of members of other groups or on the contrary value diversity as a social good); or on *strategies* (even when individuals have no taste for or against homogeneity, it may be optimal from an efficiency point of view to transact preferentially with members of one's own type if there are market imperfections[4]); or on *production function* (e.g. skills complementarities[5]).

Lazear (1999) follows the production function approach to provide a first simple theoretical foundation to the issue of workforce diversity and firm performance. In his seminal paper, he studies the interaction of different workers in global firms and points out that in order to be productivity enhancing, teams should be diverse along the dimension of skill, ability and information relevant to work tasks. On the contrary, he argues that teams should be homogenous in terms of demography, i.e. age, region or state of birth, social origin, race, etc. to avoid communication problems. Along the same line, Prat (2002) studies diversity in team theory and shows that the sign of complementarity between jobs determines the degree of workforce diversity. With positive complementarities, the team should be composed of agents of the same type, while, with negative complementarities, workforce heterogeneity is optimal. Osborne (2000) builds a model where a profit maximizing firm adjusts workforce composition to product demand variation: firms' optimal workforce composition depends on the extent to which different groups can respond to market demand.

Concerning in particular the three dimensions of interest for this paper (age, education and gender diversity) the previous literature provides different (and often opposite) theoretical results. Age diversity can lead to communication problems and misunderstanding between senior and younger workers (Lazear, 1999; Becker, 1957; Hamilton et al. 2004) with a negative reflection on firm productivity. Moreover, it undermines social ties which result in lower peer pressure (Lazear, 1999), less cohesiveness and more absenteeism (Ilmankunnas et al., 2010) and because of less (positive) rivalry also less productivity (Choi, 2007). Moreover, the literature on age workforce composition has shown that prime age workers are more productive because of younger workers’ lower experience and older workers’ loss of cognitive and physical skills (Cataldi et al. 2011). However, Choi (2007) also points out that lower social ties result in less emotional conflict in terms of career comparison and rivalry and can therefore have a positive effect on firm performance. Moreover, there can be positive

[4] Greif (1993) argues that traders in Medieval times formed coalitions along ethnic lines in order to monitor agents by exchanging information on their opportunistic behavior.

[5] Probably the most famous paper on skill complementarities is the one by Kremer (1994) on assortative skills matching, see infra.

complementarities between youth and old (e.g. Lazear, 1999) leading to knowledge transfer and mentoring.

Previous theoretical literature on education (or alternatively skill) diversity tends to suggest a positive effect thanks to complementarities between workers provided that they have separate and relevant skills (e.g. Lazear, 1999). In addition, education/skill diversity generates positive spillovers (low skilled learn from others, Hamilton et al. 2004). Moreover if education/skills diversity fosters innovation (Parrotta et al. 2010) this reflects in positive effect for firm productivity as well. On the opposite, Kremer (1993) argues that production is higher when pairing people with similar skill levels work together, i.e. assortative matching. This is so called "O'Ring theory" (the name comes from the Challenger disaster in 1986, caused by the failure of one single small component, the o'ring). Kremer's arguments would therefore suggest that education/skill diversity is negative for firms' performance.

Concerning gender diversity, previous theoretical literature is scarce. Akerlof and Kranton (2000) in their seminal paper on identity economics argue that men, especially in male dominated sectors, might dislike working with women in some jobs (they make the example of a carpenter) and hence women would suffer from increasing hostility and discrimination from threatened men (see also Haile, 2012) with a negative impact on firms performance. Since "norms" stipulate that men and women should do particular jobs, irrespective of their individual tastes and abilities, firms might find rational to "completely segregate men and women and avoid loss in productivity due to retaliation and work disruption", despite the resulting inefficient mix of workers' skill (Akerlof and Kranton, 2010). Bertrand et al. (2012) argue that, on the one hand, quotas, and hence gender diversification, could lead to patronizing and hence less effort put by women and men who feel that their effort is not worthy because in any case the post is reserved to a woman. On the other hand quotas might motivate women to put more effort once the glass ceiling has been broken and more career opportunities made available. On the opposite, studies in social cognitive theory[6], argue that gender diversity results in a better group efficacy performance (Lee and Fahr, 2004) and a better person-organization fit (women prefer more inclusive firms, Kristof, 1996) with potentially positive effects on firm productivity.

The effect of workforce diversity is likely not to be homogeneous across industries. In particular, in traditional industries with more routinary tasks, the cost of heterogeneity can be bigger than the benefits (Pull et al., 2012). In particular, Göbel and Zwick (2012) suggest that the effect of age and age diversity can change across sectors: in more innovative sectors, there are higher complementarities between younger and older workers (younger workers more knowledgeable in ICTs). Moreover, technologies foster skill update and can compensate for disabilities and physical decline and as a result increase productivity of older workers (Cataldi et al, 2011). Also gender diversity can have different effects across sectors: Akerlof and Kranton (2000) argue that men distaste for women is stronger in traditional industries (they choose the example of a female carpenter at a construction company who was "baited and teased" by a male coworker). Moreover, more high tech/knowledge intensive sectors provide

[6] Social cognitive theory, used in psychology, education, and communication, posits that portions of an individual's knowledge acquisition can be directly related to observing others within the context of social interactions, experiences, and outside media influences.

generally better working conditions for women because less physical stamina are needed, while more creative thinking, usually increasing in diversity, is appreciated (Arun and Arun, 2002). Webster (2007) argues that in high-tech/knowledge intensive sectors more soft skills are needed and women can very effectively provide them. Overall high-tech/knowledge intensive sectors generally provide less “macho” working environment and therefore gender diversity might have positive effect compared to more traditional industries. Finally, concerning education diversity, Parrotta et al. (2010b) argue that education/skills complementarities are even more relevant in innovative sectors increasing further the “returns” to education/skills diversity.

The empirical literature is somehow more developed than the theoretical one, but the results are not clear-cut. Moreover, the findings in most cases must be considered with caution due to methodological and/or data limitations. Table 1 summarizes the papers focusing on workforce diversity and performance at firm level.

[INSERT TABLE 1]

Some studies focus on a specific company to rule out unobserved factors issues constant over time, at a cost of a lower external validity. Kurtulus (2011) studies the effects of demographic dissimilarity among employees who work together within the divisions of a big US company, and non-demographic dissimilarity.

She finds evidence that age dissimilarity, dissimilarity in firm tenure, and performance dissimilarity are associated with lower worker performance, while wage differences are associated with higher worker performance[7]. Leonard and Levine (2006) also focus on one single company, with more than 800 retail stores across the US. They want to test if employee diversity affects business performance as a result of matching worker characteristics to customer characteristics or as a result of how members of a group work with each other in teams. They find little payoff to matching employee demographics to those of potential customers except when the customers do not speak English. Hamilton et al. (2004) use panel data with individual productivity data from a garment plant in California which shifted from individual piece rate to group piece rate production over three years. Their results indicate that teams with more heterogeneous worker abilities are more productive and teams with greater diversity in age are less productive, and those composed only of one ethnicity (Hispanic workers) are more productive (however, the findings for team demographics are not robust to alternative model specifications). Mas and Moretti (2009) study peer effects in a supermarket chain and they find positive spillovers implying that skill diversity is beneficial.

Another strand of studies relies on large linked employer employee panel dataset (LEEDs). LEEDs allow studying the connections between workforce characteristics and productivity at the plant- or firm level by using the rich set of information on both worker characteristics (age, gender, tenure, education, etc.) and firm characteristics which may impact firm- or plant-level productivity. Navon (2009) studies the relationship of human capital spillovers,

[7] Her analysis also reveals that the effects of certain types of dissimilarities get smaller in magnitude the longer a worker is a part of a division. Finally, the paper provides evidence that the relationships between performance and the various measures of dissimilarity vary by occupational area and division size.

and hence education diversity, and productivity using a dataset for Israel and finds a beneficial effect of education diversity.

Barrington and Troske (2001) build a unique diversity measure of race and gender and find no or positive effect in the USA. Grund and Westergaard-Nielsen (2008), using LEED for Denmark, find that both mean age and dispersion of age in firms are inversely U-shaped related to firm performance. Haile (2012) studies employee job-related well-being in Britain and finds a negative effect of gender diversity on job well-being for women because of increasing hostility and discrimination from the "threatened" men.

More similar to our paper in terms of empirical strategy and data used are the ones by Ilmakunnas and Ilmakunnas (2011) and Parrotta et al. (2010). Ilmakunnas and Ilmakunnas (2011), contrary to the predictions of the theoretical literature, find a negative effect of education diversity on productivity and a positive one of age diversity in Finland using fixed effects, GMM, and Olley-Pakes (1996) approach. Ilmakunnas and Ilmakunnas (2011) also find some positive effect of age on individual wages. Parrotta et al. (2010) run a similar analysis for Denmark and also go deeper in the estimation technique by instrumenting worker diversity with workforce characteristics in the area where the firm is based (assuming therefore no strategic choice by firms of the area where to install the plant). They find evidence that labour diversity in skills/education significantly enhances firm performance as measured by firm TFP while diversity in demographics and ethnicity brings mixed results.

Other studies adopt a different point of view: Cook and Glass (2011), for instance, study the reaction of stock prices to a ethnic diversity award and they find different results according to the ethnicity considered: black and Hispanic are negatively related to share price reaction while Asian workers are positively related. Kahane et al. (2012) study the US National Hockey League teams' diversity and they find a positive effect of the presence of European players (from a single European country, while having players from several European countries is detrimental) on team results. Hoogendoorn et al. (2011) and Hoogendoorn and Van Praag (2012) run a randomized experiment in a business school in Denmark and find a positive effect of gender diversity and ethnic diversity (if at least the majority of team members is ethnically diverse) of management teams on simulated firm performance.

HRM research usually adopts a larger focus compared to the relative narrow one in economics: in HRM literature diversity also covers sexual orientation, disability, race (see Shore et al., 2009 for a complete overview) and also network ties and team dynamics and commitment to common values (see Horwitz and Horwitz, 2007 and Roberge and van Dick, 2010 for a summary). Also the set of diversity concepts, and hence measures, is richer in HRM and sociological studies.[8] HRM and sociological literature also analyses a broader set of outcomes: whereas economics has focused mainly on productivity (in a large sense), HRM also includes more qualitative analysis at individual (organizational commitment, turnover or

[8] Harrison and Klein (2007) in their methodological paper distinguish three dimensions: separation, variety and disparity. *Separation* refers to horizontal distance (along a single continuum representing dissimilarity in a particular characteristic, e.g. age, or attitude); *variety* refers to differences in kind or category, primarily of information, knowledge, or experience among unit members but also of gender; and *disparity* refers to differences in concentration of valued social assets or resources such as pay and status among unit members- vertical differences that, at their extreme, privilege a few over many.

turnover intentions, individual creativity and frequency of communication) and company level, e.g. by using financial indicators or team-member ratings of team effectiveness (see review by Jackson et al., 2003). Overall, in HRM and sociological literature two main views are opposed.[9] One puts forward a "business case for diversity" (Cox, 1993) according to which diversity pays and represents a compelling interest for employers. Another refuses the business case and sees diversity as "a process loss" because of the conflict arising and as a result absenteeism and turnover increase. A third view has arisen to try smoothing the differences by pointing at creative outcomes of the conflict (by closer examination, more complex learning environment and stronger peer pressure) or by increasing contacts, information sources, creativity, and innovation. The benefits of diversity may extend beyond team and workplace functioning and problem solving (Choi, 2007). Sen and Bhattacharya (2001), for instance, propose that diversity influences consumers' perceptions and purchasing practices. The literature also points out more complex mechanisms and asymmetries: Chattopadhyay (1999) finds that age dissimilarity varies in direction for older and younger employees, with better performance for youth in an age-homogenous environment.

To summarize, theoretical literature provides contrasting predictions of the effect of age, education and gender diversity on firms' performance according to the type of mechanisms and interactions taken into account. The empirical economic research also provides mixed results. Moreover, most papers should be considered with caution due to methodological and data limitations. Only three papers to our knowledge correct for endogeneity either using GMM or IV or more structural approaches whereas two use an experimental design as can be clearly seen in Table 1. The aim of this paper is to overcome some of these limitations by using two diversity measures (plus one specific to gender) and applying the analysis to a large representative data set through sound microeconomic tools.

Moreover, all the studies published so far, except Ilmakunnas and Ilmakunnas (2011) who estimate the impact on individual wages, have concentrated only on the productivity side, suggesting that they are primarily concerned with the effect of diversity on firms' productivity or growth at a more aggregate level. This paper focuses also on the rent sharing of diversity and the effect on wages. Finally, no paper, to our knowledge, studies the possibly different impact of diversity in different sectors.

3. The estimation strategy

In this paper we study the impact of workforce diversity by estimating a production function and a wage equation, both expanded by the specification of a labour-quality component. This technique was pioneered by Hellerstein and Neumark (1995) and further refined and applied in Hellerstein et al. (1999) and by many others with respect to groups of workers in terms of age (e.g. Cataldi et al., 2011), age and gender (e.g. Vandenberghe, 2012), type of contract (e.g. Cataldi et al. 2012), occupations (e.g. Kampelmann and Rycx, 2012), but also gender wage discrimination (Vandenberghe, 2011). In this paper, we apply it to analyse the impact of workforce diversity on productivity and wages.

[9] For a complete overview of the literature see Ilmakunnas and Ilmakunnas (2011).

In order to estimate the impact of workforce diversity on productivity, we start by taking a function linking a range of inputs of firm *i* to its added value:

$$Y_{i,t} = F(K_{i,t}, QL_{i,t}) \qquad (1)$$

where $Y_{i,t}$ represents value-added, $K_{i,t}$ the firm's capital stock and $QL_{i,t}$ is a quality of labour term. The latter allows introducing a heterogeneous labour force into the value-added function.

There is an abundant econometric literature on the estimation of relationships as the one depicted in equation (1). Various authors have proposed different specifications, allowing e.g. for different elasticities of substitution between the factors of production, in order to reflect more accurately the production process inside the firm. However, our focus is not on the production process itself, but rather on the comparison between workforce characteristics and diversity. We use a simple Cobb-Douglas version of equation (1), with substitution elasticities equal to one and the assumption of firms operating at the efficiency frontier. Such assumptions do not appear problematic as previous firm-level studies have shown that productivity coefficients obtained with a Cobb-Douglas structure are robust to other functional specifications (see, e.g. Hellerstein and Neumark, 2004). Equation (2) is the basic log-linearized (Cobb-Douglas) value-added function:

$$\log(Y_{i,t}) = \log(A_{i,t}) + \alpha log\left(K_{i,t}\right) + \beta log(QL_{i,t}) \qquad (2)$$

where $A_{i,t}$ is a Hicks-neutral technological factor and the parameters α and β are the respective marginal productivities of each input factor.

The key variable in this production function is the quality of labour $QL_{i,t}$. Following Iranzo et al. (2008), Q, the quality of labour (or efficiency of the labour force), can be expressed as a general CES production function of workers' characteristics *c* (in our case, age, education and gender):

$$\mathrm{Q(c)} = \left[\frac{1}{N}\sum_{i=1}^{N} c_i^{\gamma}\right]^{\frac{1}{\gamma}} \qquad (3)$$

As Iranzo et al. (2008) show, the importance of workforce diversity (they refer to skill dispersion) can be seen more clearly by rewriting eq. (3) through a Taylor expansion as a function of the first and second moments of workforce characteristics distribution:

$$\mathrm{Q(c)} = \bar{c} + \frac{1}{2}(\gamma - 1)\frac{\sigma^2}{\bar{c}} \qquad (4)$$

Therefore, in our empirical specification, we are going to estimate a value-added function where we control for the first and second moments of workforce characteristics of interest and a set of other controls. To ensure the consistency and the comparability of the results we also estimate an extended Mincer equation at firm level[10] on the same set of variable of interest and controls.

In line with Ilmakunnas and Ilmakunnas (2011) and Parrotta et al. (2010), the model for value-added in eq. (5) and wages in eq. (6) based on the developments of the theoretical framework in eq. (4) is our baseline specification:

$$\log\left(\frac{VA}{h}_{\mathrm{i,t}}\right) = \alpha + \beta_1 A^{\sigma}_{\mathrm{i,t}} + \beta_2 E^{\sigma}_{\mathrm{i,t}} + \beta_3 G^{\sigma}_{\mathrm{i,t}} + \beta_4 \overline{A}_{\mathrm{i,t}} + \beta_5 \overline{E}_{\mathrm{i,t}} + \lambda X_{\mathrm{i,t}} + s_{\mathrm{i}} + y_{\mathrm{t}} + \varepsilon_{\mathrm{i,t}} \quad (5)$$

$$\log\left(\frac{W}{h}_{\mathrm{i,t}}\right) = \alpha^* + \beta^*_1 A^{\sigma}_{\mathrm{i,t}} + \beta^*_2 E^{\sigma}_{\mathrm{i,t}} + \beta^*_3 G^{\sigma}_{\mathrm{i,t}} + \beta^*_4 \overline{A}_{\mathrm{i,t}} + \beta^*_5 \overline{E}_{\mathrm{i,t}} + \lambda^* X_{\mathrm{i,t}} + s_{\mathrm{i}} + y_{\mathrm{t}} + \varepsilon^*_{\mathrm{i,t}} \quad (6)$$

The dependent variable in equation (5) is firm *i*'s value added in hourly terms, obtained by dividing the total value added by the firm *i* in period *t* by the total number of hours worked that have been declared for the same period. In equation (6), the dependent variable 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 declared work hours.

The main variables of interest are $A^{\sigma}_{i,t}$, $E^{\sigma}_{i,t}$, $G^{\sigma}_{i,t}$, being respectively age diversity, education diversity and gender diversity which capture the effect of diversity on productivity and wages. $\bar{A}_{i,t}$ and $\bar{E}_{i,t}$are respectively average age and years of education. $X_{i,t}$ represents other controls (share of non-standard employees, share of white collars, share of part-timers, share of workers with at least 10 years of tenure, firm size in terms of employees and firm capital). s_i are sector dummies and $\mathrm{y_t}$ year dummies. $\varepsilon_{i,t}$ and $\varepsilon^*_{i,t}$ represent the error terms.

Therefore, β_1, β_2 and β_3 are the coefficient of interest: in equation (5) they represent the impact of workforce diversity in terms of respectively age, education and gender on average firm level hourly productivity. In equation (6), β^*_1, β^*_2 and β^*_3 represent the impact of workforce diversity on the average firm level hourly wage.

Estimating equations (5) and (6) yields insights into the size and significance of the effect of diversity on productivity wage, but it does not allow to test directly whether the difference between the value added and wage coefficients 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 average wage is regressed on the same set of explanatory variables as in equations (5) and (6):

$$\log\left(\frac{VA}{h}_{\mathrm{i,t}} - \frac{W}{h}_{\mathrm{i,t}}\right) = \tilde{\alpha} + \widetilde{\beta_1} A^{\sigma}_{\mathrm{i,t}} + \widetilde{\beta_2} E^{\sigma}_{\mathrm{i,t}} + \widetilde{\beta_3} G^{\sigma}_{\mathrm{i,t}} + \widetilde{\beta_4} \overline{A}^{\sigma}_{\mathrm{i,t}} + \widetilde{\beta_5} \overline{E}^{\sigma}_{\mathrm{i,t}} + \tilde{\lambda} X_{\mathrm{i,t}} + s_{\mathrm{i}} + y_{\mathrm{t}} + \widetilde{\varepsilon_{\mathrm{i,t}}} \quad (7)$$

The $\tilde{\beta}$s, in this case, estimate the size and significance of productivity-wage gap for each diversity dimension.

[10] Ilmakunnas and Ilmakunnas (2011), the only other paper looking also at the impact of workforce diversity on wages, estimate productivity at firm level and wages at the individual level.

From an econometric point of view, we first estimate the value-added function and the wage equation by pooled OLS (we use a Huber/White/sandwich estimate of variance, i.e. the errors are robust to heteroscedasticity and serial correlation; see Wooldridge, 2002). This estimator is based on both the cross-section variability between firms and the longitudinal variability within firms over time. A further point to consider for the econometric specification is that information in the SES refers to the month of October of 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) that on explanatory variables, all explanatory variables in equations (5), (6) and (7) have been lagged by one year. In this way, information on firm's and workers' characteristics relative to the month of October in year *t* is used to explain firm-level productivity in year *t+1*.

However, OLS do not solve for bias due to firm unobservables: productivity depends to a large extent on firm-specific, time-invariant characteristics that are not measured in micro-level surveys. More formally the residuals $\varepsilon_{i,t}$ in equations (5), (6) and (7) can be decomposed as $\varepsilon_{i,t} = \vartheta_i + \omega_{i,t} + \eta_{i,t}$ where ϑ_i represents firm fixed effects, $\omega_{i,t}$ represents shocks observed by the firm but not by the econometrician and $\eta_{i,t}$ idiosyncratic shocks not observed neither by the firm nor by the econometrician. As a consequence, the coefficients of these estimators might be biased. There might be a heterogeneity bias due to factors such as an advantageous location, firm-specific assets like the ownership of a patent, other firm idiosyncrasies. There might (also) be a endogeneity bias due simultaneity between firm productivity and workforce diversity (for instance, most productive firms might choose or attract a more diverse workforce).

Firm fixed effects (or first differences) could help controlling for ϑ_i, i.e. firm specificities constant over time such as advantageous location, patents etc. and hence solving for heterogeneity bias. However, as for Parrotta et al. (2010), fixed effects are not very suitable in this framework because they exploit only the across time variation within each firm (quite low in Belgium across the observed years) leaving substantial information (the cross-sectoral ones) unused and, in any case, do not control for time-varying $\omega_{i,t}$.

IV techniques or natural experiments could help controlling for $\omega_{i,t}$, and hence solving for endogeneity bias, but it is difficult to find variables fulfilling the IV requirements or natural experiments affecting exogenously the workforce diversity.[11] Therefore, a common technique in the literature refers to the dynamic panel data literature and use system GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998). Such estimator allows addressing the endogeneity of explanatory variables[12] and to control for firm fixed effects. GMM system estimator is a suitable estimation method in case of endogenous variables and it is largely used in the production function literature. For productivity estimation (eq. 5) we also adopt a more structural identification strategy implemented by Olley-Pakes (1996),

[11] There has been a pension reform in Belgium in 1997 but gradually spread all over the period of observation until 2009.

[12] Technically, variables in the differenced equation are instrumented by their lagged levels and variables in the level equation are instrumented by their lagged differences.

henceforth OP, and refined by Levinsohn and Petrin (2003), henceforth LP, which is suitable for panel with short *t* and long *N*. This technique corrects for endogeneity and firm fixed effects by developing a dynamic model and use material inputs as instruments[13] (goods and services, other than fixed assets, used as inputs into the production process, i.e. raw materials, electricity etc). Firms can swiftly respond to productivity shocks (unobserved by the econometrician but observed by the managers or owners) by adapting the volume of the intermediate inputs they buy on the market and hence inputs can be used as a proxy for $\omega_{i,t}$.

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[14]. 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, level of collective wage bargaining) and on the individuals working there (e.g. age, education, tenure, gross earnings, paid hours, sex, occupation).[15] The SES provides no financial information. Therefore, it has been merged with a firm-level survey, the "Structure of Business Survey" (SBS). The SBS,

[13] In the basic setup, there is a fully variable input, labour, and a fixed (determined in the beginning of the period) input, capital. Assuming that a proxy (investments or material inputs) depends on capital and the unobservable productivity, this relationship can be solved for the productivity term. OP use investments. However, the investment variable is very lumpy due to the related considerable adjustment costs and can only be used when observations are positive with a consistent loss of observations. Moreover, LP argue that the investment proxy may not smoothly respond to the productivity shock and then estimate parameters may be inconsistent. Then, LP propose to proxy the symmetrically observed time-varying productivity shock by using intermediate inputs. Our case differs from the basic setup. We do need to estimate the input coefficients and can directly estimate the coefficients of the demographic variables (see Appendix 2 in Ilmakunnas and Ilmakunnas, 2011 for full details).

[14] 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).

[15] 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 total firm 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).

also conducted by Statistics Belgium, provides information on financial variables such as firm-level 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 Intermediation (NACE 67). The merge of the SES and SBS data sets has been carried out by Statistics Belgium using firms' social security numbers. In contrast to firms, workers cannot be followed over time in our data set. Hence, we are able to control for firms' but not for workers' fixed unobserved heterogeneity.

Three filters have been applied to the original data set. The first derives its rationale from neoclassical productivity theory, which relies on the assumption that prices are economically meaningful. This is why we deleted firms that are publicly controlled and/or operating in predominantly public sectors from our sample. All regressions are therefore applied to privately controlled firms only.[16] Second, we have eliminated firms with less than 10 employees, the reason for this being our use of first and second moments of workers' characteristics at the firm level. In order to assure that averages and variances are based on a minimum number of observations, we filtered out firms that provided information on less than ten employees.[17] In addition to applying these two filters, the final sample on which our estimations are based consists only of firms that are observed in at least three consecutive years due to the inclusion of lagged differences in our models. This leads to a bias towards big firms because of the sample design of the SES in which big firms are more likely to stay in the sample for several consecutive years than small firms. Third, we exclude workers and firms for which data are missing or inaccurate.[18]

Our final sample consists of an unbalanced panel of 2,431 firms yielding 7,463 firm-year-observations during the 7-year period (1999-2006). It is representative of all medium-sized and large firms within sections C to K of the NACE Rev. 1 nomenclature, with the exception of large parts of the financial sector (NACE J) and almost all the electricity, gas and water supply industry (NACE E). The average number of observations per firm in each year is around 35.

The definition of earnings we use in the estimation correspond to the total gross wages, including premia for overtime, weekend and nightwork, performance bonuses, commissions and other premia. The work hours correspond to the total remunerated hours in the reference period (including paid overtime hours). The firm's value added per hour is measured at factor costs and calculated with the total number of hours effectively worked by the firm's employees. All variables in the SES-SBS are not self-reported by the employees, but provided by the firm's management and therefore more precise compared to employee or household surveys.

The variables of (main) interest are age, education and gender diversity. Two indicators of diversity are used: standard deviation and dissimilarity index. The standard deviations of the

[16] More precisely, we eliminate firms for which public financial control exceeds 50%. This exclusion reduces the sample size by less than 4%.
[17] This selection is unlikely to affect our results as it leads to a small drop in sample size.
[18] For instance, we eliminate a (very small) number of firms for which the recorded value added was negative.

workers characteristics is a measure of dispersion of the workforce. The dissimilarity index (already quite popular in diversity research in psychology and human resource management but less in economics), or Euclidean distance, is a measure of *relational demography*[19]. It can be computed as the square root of the sum of firm variance and square deviation from the firm mean. If x_i denotes the characteristics of individual *i* and there are *N* individuals the index is:

$$diss_i = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(x_i - x_k)^2} = \sqrt{(x_i - \bar{x})^2 + Var(x)} \qquad (8)$$

Moreover, we also use the gender diversity index, i.e. the share of women times the share of men (Hoogendoorn et al., 2011). All diversity indexes share the property that diversity is maximal when the employees are evenly divided to the extremes of the distribution and minimal when all of them are equal.[20]

Since firms' capital stock is not available in the SES-SBS data set, capital is computed through the widely used *perpetual inventory method* (or PIM, see OECD, 2009 for more details). The PIM rests on the simple idea that capital stocks constitute flows of investment (available in the SBS data set), corrected for retirement and efficiency loss, assuming a depreciation of capital of 0.05 per year.

[INSERT TABLE 2]

Table 2 sets out the means and standard deviations of the variables of interest in this paper. We observe that firms have a mean value added per hour worked of 61.06 euros and that workers' mean gross hourly wage stands at 17.14 euros. The workers in the sale have an average of 11.44 years of education (corresponding to upper secondary education) and an average age of 38.4 and they are on majority men (73 percent). The two diversity indicators used (standard deviation and dissimilarity index) show (see Table 2) that firms tend to employ a strongly diverse workforce in term of age, less so in terms of education and even less in terms of gender. Average workforce diversity is pretty constant over the time period observed. In our sample, 45 per cent of hours are worked by white collar workers[21], and 4 per cent of hours by people on non open-ended employment contracts. Overall, 65 per cent of workers in our sample are employed in relatively big firms (i.e. firms with at least 100 employees) and are essentially concentrated in the manufacturing sector (57 percent), wholesale and retail trade, repair of motor vehicles, motorcycles and personal and household goods (12 percent), construction (10 percent) and real estate, renting and business activities (11 percent).

5. Results

This section presents the results of the empirical analysis. First, we estimate productivity and wages and the productivity-wage gap with OLS and GMM and as a robustness check we also

[19] The dissimilarity index allows the diversity effects to vary according to the degree to which the individuals are different from their peers.
[20] This is not the case when using the share of workers as some papers do (see Table 1 for full references).
[21] White collars are defined as managers (ISCO 1), professionals (ISCO 2), technicians and associate professionals (ISCO 3), clerks (ISCO 4), service workers and shop and market sales workers (ISCO 5).

estimate productivity with the method developed by Olley and Pakes (1996) and refined by Levinsohn and Petrin (2003). Secondly, we run the same estimates differentiating between firms in different technological environment to check if diversity has the effects in more innovative firms as in more traditional ones.

5.1 Workforce diversity, productivity, wages and productivity-wage gap

Table 3 presents the parameter estimates of the average productivity (equation 5), wages (equation 6) and productivity-wage gap (7), under three alternative econometric specifications. Note that, with equation (7) being the difference between equation (5) and equation (6), it is easy to verify that $\beta - \beta^{*} \simeq \tilde{\beta}$ for each regressor.

The first panel of Table (3) shows the estimates using OLS. Age diversity has a negative effect both on firm productivity and wages. Firms with a more diverse workforce in terms of age tend to have a lower productivity: when age standard deviation increases by one year, productivity decreases on average by 0.9 percent (corresponding to 1.63 standard deviation for comparison purposes[22]) and wages by 1 percent (1.82 standard deviation).

[INSERT TABLE 3]

On the other hand, education diversity has a positive and significant impact on productivity and wages: when in a firm the education standard deviation increases by 1 year, productivity increases by 3.7 percent (or 3.1 standard deviation) and wages by 3.4 percent (or 2.85 standard deviation). Gender diversity has no significant impact on firm productivity but a negative one on wages: an increase by 1 standard deviation increases wages by 16.3 percent (or 2.44 standard deviation).

The estimated coefficients for the productivity and wage equations are very similar in size, suggesting that the benefits or loss of workforce diversity are shared between firms and employees. This is confirmed by the estimations of eq. (7) in column (3) of Table 3 which shows that there is no productivity-wage gap. Therefore, according to OLS estimates, there is no wage premium or firm mark-up from diversity. The OLS estimates also find a significant and positive effect of average age and average education years on productivity and wages.

OLS estimates should be interpreted with caution. Heterogeneity bias might be present since our sample covers all sectors of the Belgian private economy and the list of controls included in our models cannot cover all characteristics. Even if the introduction of the set of dummies (year and sector) can wipe out part of this heterogeneity bias, still time-invariant firm's characteristics are not taken into account. However, even fixed effects or first differences would not be fully sufficient. The endogeneity in labour input choices is well documented problem in the production function estimation literature (e.g. Griliches and Mairesse, 1995): workforce diversity might be endogenous since more productive firms might choose or attract a more diverse workforce (or less diverse). To address this issue, controlling at the same time

[22] Age, education and gender diversity have very different patterns and the coefficients in the Tables are not directly comparable. For instance an increase of 1 point in age standard deviation does not represent a major shift. On the other hand an increase of 1 point in gender standard deviation would represent a major change (see descriptive statistics in Table 2).

for firm fixed effects and diversity endogeneity, we estimate our model using the static[23] system GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998). To examine the reliability of the corresponding estimates, we first apply the Hansen test (or J-test) of overidentifying restrictions and the Arellano-Bond (1991) test for second-order autocorrelation in the first-difference errors. The null hypothesis for the Hansen is that the instruments are jointly valid (i.e., uncorrelated with the error term), and that the instruments are correctly "excluded" from the estimated equation. Under the null, the test statistic is distributed as chi-square in the number of overidentifying restrictions. A failure to reject the null hypothesis (high p-values) implies that the instruments are exogenous. Secondly, GMM estimator requires, for the validity of the instruments, that there is first-order serial correlation and more importantly that there is no second-order serial correlation in the residuals. Since the null hypothesis is that there is no second-order serial correlation, it means that one needs not to reject it to get appropriate diagnostics (high p-value). As shown at the bottom of the second panel of Table 2, the Hansen test and the Arellano-Bond test respectively do not reject the null hypothesis of valid instruments and of no autocorrelation.

Results with GMM in the second panel of Table 3 show that, as for OLS estimates, age diversity has a negative and significant impact on both productivity and wages. Education diversity has a positive but, opposite to previous results, not significant impact on productivity but it has some positive and significant effect on wages. Gender diversity has a strongly negative impact on both productivity and wages: when gender standard deviation increases by one, productivity decreases by 3.9 standard deviation and wages by 2.1 standard deviation. The estimate in column (3) shows no major productivity-wage gap: only age diversity produces a slightly significant negative coefficient pointing to the presence of a minor premium for workers.

We now test the robustness of productivity estimations using the technique developed by Olley-Pakes (1996) and refined by Levinsohn and Petrin (2003). When estimating OP, there is a consistent loss of observations.[24] Therefore we estimate equation (7) using as an instrument material inputs which, as suggested by LP, are less lumpy than investments (we lose just 2 observations).

Column (7) in Table 3 shows estimations with LP. Age diversity is not significant while education diversity has a positive and significant impact of firm productivity: an increase in 1 point education standard deviation increases productivity by 3.2 percent (or by 2 standard deviations). Gender diversity as for OLS and GMM has a negative and significant impact on firms productivity: an increase of 1 point in gender standard deviation increases productivity by 11.3 percent (or 1.6 standard deviation).

[INSERT TABLE 4]

Results are also robust to different specifications. Table 4 presents the estimates for value-added, wages and productivity-wage gap using the dissimilarity index as specified in equation

[23] We also estimated a dynamic model with very similar results but the wage equation does not pass the test for overidentifying restrictions.
[24] We would lose almost 40 percent of the observations of the OLS and GMM sample because of missing or 0 investment.

(8). The results are very much in line with the previous ones with standard deviation: age and gender diversity have a significant impact on productivity (OLS for age, GMM for both and LP for gender) and on wages (OLS and GMM). Education diversity has a significant and positive impact on productivity using LP and on wages. Overall also estimates using the dissimilarity index show no sign of major productivity-wage gap (just a small underpayment for age diversity). Moreover, all results are fully consistent when using the gender diversity index (share of women times share of men) as Table A.1 shows.

Workforce might have a non-linear effect (with the presence of a threshold) on productivity and wages. Indeed, diversity might be beneficial up to a certain point and then have negative effects or the reverse. Therefore, we have also estimated a specification with second order polynomial and another specification where diversity indicators or diversity indicators interacted with a dummy equal to one when the diversity indicator is above the 50th or the 66th percentile. In all specifications the resulting coefficients are not significant pointing to no sizeable threshold effect of workforce diversity on productivity and wages (see Table A.2 in Annex). What is more, there might be interaction effects between different diversity dimensions: for instance, Vandenberghe (2012) finds a negative effect of a greying and feminizing workforce on productivity in Belgium using a firm-level panel dataset. If we estimate equation (5), (6) and (7) taking out age diversity or gender diversity or interacting the two or interacting age diversity with the share of women, the results do not vary[25]. We conclude, therefore, that there are not sizeable interaction effects of age and gender diversity in the firms in our sample.

In conclusion, these baseline estimates correcting for endogeneity bias with GMM and Levinsohn-Petrin approach and using several specifications and diversity indexes suggest that demographic diversity, i.e. age and gender, has a negative impact on productivity and wages while education diversity has a positive impact on productivity and wages without major productivity-wage gaps.

These results are in line with theoretical predictions which point out negative effects of age on firm productivity due to misunderstandings and communication problems (Lazear, 1999; Becker, 1957; Hamilton et al. 2004), lower peer pressure (Lazear, 1999), lower social ties and hence lower cohesiveness and more absenteeism (Ilmakunnas et al., 2010) or lower productivity because of lower experience for youth and loss of cognitive skills for older workers. Since in our sample we have a majority of “man dominated sectors” (for instance, we do not cover the public sector which is a major pool for female employment), the negative effect of gender diversity can be the result of the distaste of men working with women (Akerlof and Kranton, 2000) and hence increasing hostility and discrimination from threatened men (Haile, 2012; Akerlof and Kranton, 2000). On the opposite, the positive effect of education diversity can be explained in terms of skill complementarities (Lazear, 1999) and intra-firm spillovers (low skilled learn from others, Hamilton et al. 2004). We now test if these results are invariant across sectors.

[25] Results available upon request.

5.2 Does the technological environment matter?

As argued in the literature review, the relationship between workforce diversity and productivity is likely to differ across firms: certain characteristics of the work environment such as routinary tasks or the use of innovative technologies can interact differently with workforce composition.

Given the non-existent empirical evidence on the link between workforce diversity and the technological environment, this section presents 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 the taxonomy developed by Eurostat, according to the technological intensity (R&D spending/value added) of each sector at NACE 2 or 3 level[26].

Applied to our sample, this Eurostat taxonomy of high-medium tech/knowledge intensive sectors classifies 679 firms as HT/KIS and 1,778 as non- HT/KIS firms[27]. As seen in the descriptive statistics, these two types differ along several dimensions (see Table 2). Average hourly value added and hourly wages are higher in HT/KIS compared to non-HT/KIS firms, in line with the intuition that HT/KIS firms are in general more productive. However, firms in HT/KIS sectors have a higher capital and invest significantly more. Differences in the educational and occupational composition also exist: the workforce of HT/KIS firms is on average much more educated and more concentrated in white collar occupations compared to non-HT/KIS firms. Interestingly, HT/KIS firms are also characterised by a more feminine labour force. Moreover, it is noteworthy that both HT/KIS and non-HT/KIS employment is

[26] *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). The detailed taxonomy can be found at http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/Annexes/hrst_st_esms_an9.pdf

[27] 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.

predominantly concentrated in the manufacturing sector (respectively around 53 and 58 percent), while more than one third of workers employed in HT/KIS firms is also found in real estate, renting and business activities (around 37 percent). By contrast, the age composition of the two sectors hardly differs: although HT/KIS firms have a somewhat younger labour force, the average age is relatively close.

To test formally for differences between HT/KIS and non-HT/KIS firms, we add to our baseline model: 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. Equation (5) becomes:

$$\log\left(\frac{VA}{h}_{\mathrm{i,t}}\right) = \alpha + \beta_1 \mathrm{A}^{\sigma}_{\mathrm{i,t}} + \beta_2 \mathrm{E}^{\sigma}_{\mathrm{i,t}} + \beta_3 \mathrm{G}^{\sigma}_{\mathrm{i,t}} + \beta_4 \overline{\mathrm{A}}_{\mathrm{i,t}} + \beta_5 \overline{\mathrm{E}}_{\mathrm{i,t}} + \beta_7 \mathrm{A}^{\sigma}_{\mathrm{i,t}} * \mathrm{ICT} + \beta_8 \mathrm{E}^{\sigma}_{\mathrm{i,t}} * \mathrm{HT/KIS} + \beta_9 \mathrm{G}^{\sigma}_{\mathrm{i,t}} * \mathrm{HT/KIS} + \beta_{10} \overline{\mathrm{A}}_{\mathrm{i,t}} * \mathrm{HT/KIS} + \beta_{11} \overline{\mathrm{E}}_{\mathrm{i,t}} * \mathrm{HT/KIS} + \kappa\, \mathrm{HT/KIS} + \lambda \mathrm{X}_{\mathrm{i,t}} + \mathrm{s_i} + \mathrm{y_t} + \varepsilon_{\mathrm{i,t}} \quad (9)$$

and similarly equations (6) and (7).

[INSERT TABLE 5]

Table 5 shows the estimates using OLS, GMM and LP method. Again, we find that age diversity has a negative effect both on firm productivity and wages. However, GMM estimate shows that for firms in HT/KIS-intensive sectors gender diversity has a positive and significant impact on productivity but not on wages (an increase by 1 point in age standard deviation increases productivity by 38.9 percent, or for comparison purposes 5.83 standard deviation) while LP estimates yield a lower impact (14.8 percent or 2.22 standard deviation). HT/KIS sectors probably provide women more comfortable and less “macho” working conditions (an easy example would be to compare services to construction or transports). Likely, HT/KIS sectors rely also less on physical stamina and more on creative working than other traditional non-HT/KIS sectors and therefore women's contribution and perspective can be necessary and appreciated (see Arun and Arun, 2002). In HT/KIS sectors the share of women is higher than in non-HT/KIS sectors (33% vs. 24%) which suggests, following Akerlof and Kranton (2010), that jobs in HT/KIS sectors are less male dominated and then risks of retaliation or work disruption are lower when more women are employed there than in more traditional “male jobs”. Moreover, according to Webster (2007), there is a growing demand for “soft” skills in HT/KIS work which women can provide very effectively (business skills, communication skills, team-working skills, competencies, personal attributes, individual qualities, transferable skills, social skills, interpersonal skills) for client-facing work and for managing outsourcing relationships on which the HT/KIS sector is strongly dependent.

Education diversity has a positive effect also on wages: an increase in gender standard deviation increases wages by 4 percent (or 3.36 standard deviation). Overall, the coefficients of estimates for the productivity and wage equations are again very similar in size to the impact on productivity, but for age diversity, suggesting that the benefits or loss of workforce diversity are evenly shared between firms and employees. Column (6) of Table 5 shows that there is no sizeable productivity-wage gap. Again, results are fully consistent using the dissimilarity index (see Table 6).

[INSERT TABLE 6]

We also check the robustness of our results using other taxonomies to distinguish between more innovative and more traditional firms. We use the taxonomy by Eurostat of knowledge intensive activities (KIA) and non-KIA and the one developed by O'Mahony and van Ark (2003) of ICT and non-ICT firms (see Appendix B for more details). Results in Table A.3 and Table A.4 are very consistent despite strong differences between the taxonomies (correlation coefficients are quite low, see Table B.1). With ICT we also find a significant and positive effect of age diversity in a more innovative intensive sectors. Moreover, our results are not simply driven by the division between manufacturing and services: Table A.5 shows the results of equation (9) using a dummy for services. GMM estimates both with standard deviation and dissimilarity index do not show any difference between manufacturing and services. Nor these results are driven by the size of the firm: we have run several estimates with different cut-off (75, 100, 125, 150 employees) and there are no significant differences between smaller and bigger firms.[28]

Yet, it should be noted that our results do not allow making any definite statement about the causality of the observed correlations. The point is that "being HT/KIS" may not be considered as an exogenous treatment that can be assimilated to a natural experiment. As a result, what we interpret as the direct impact of the technological environment on the productivity and wages is only one of many mechanisms that may affect the productivity and wage profiles of HT/KIS and non-HT/KIS firms.

This being said, our model accounts for some of such indirect factors by controlling for a number of firm and workforce characteristics. Moreover, as Cataldi et al. (2012) argue, this issue may be less of a problem when using the productivity-wage gap as a dependent variable, as one could assume that the remaining bias could be present in both productivity and pay measurements and hence be cancelled out in the difference. Finally, it should be noted that the approach presented in this paper addresses a range of measurement issues that improve considerably the reliability of estimation results compared to existing research.

Therefore, we can conclude that, in line with previous theoretical predictions, demographic diversity has a negative effect on productivity and wages with no significant gap in traditional industries, while in more innovative industries also gender and age diversity are a positive factor for firm's productivity and wages.

6. Conclusions

Workforce diversity is an increasingly important issue in human resource management. Changes in demographics (ageing, migration, and women empowerment) and in social preferences (the value of diversity per se is strengthening in all developed countries) are forcing firms to deal with increasing workforce diversity. Therefore managing properly

[28] Results available upon request.

workforce diversity is becoming a priority for many companies. Theoretical literature predicts that diversity can be beneficial for firms if it fosters complementarities and/or generate spillovers or even simply create a more enjoyable working place. However, diversity is also likely to lead to misunderstandings and personal conflicts which would harm productivity and profits. Similarly, workers benefit (or lose) from higher (or lower) wages driven by productivity (on top of a more, or less, enjoyable working environment). The empirical literature on the subject is however still relatively limited and not conclusive.

This paper develops a microeconometric approach to gauge the effect of workforce diversity in terms of age, education and gender on productivity at firm level. It also adds to previous research by examining whether costs and benefits are equally shared between firms and workers by studying the effect on wages and on productivity-wage gaps. To do so, we use longitudinal matched employer-employee data covering the Belgian private sector over the period 1999-2006. Controlling for simultaneity issues and time-invariant unobserved workplace characteristics using system GMM and Levinsohn and Petrin (2003) estimators we find that i) demographic diversity, measured in terms of age and gender, has detrimental effects on firm productivity and worker wages, ii) education diversity has positive effects on productivity (with LP estimates) and wages, iii) there are no sizeable productivity-wage gaps (but a very small overpayment for age diversity). These results are consistent with the theoretical findings which predict a negative impact of age and gender diversity because of increasing misunderstandings and communication problems and lower social ties.[29] Moreover, results show that benefits and costs are equally shared between firms and workers.

However, the effects of diversity are not homogenous across all industries. Our results suggest that the effect of diversity changes according to the type of work environment: in high-tech/knowledge intensive industries gender diversity is a positive factor for firm's productivity and wages. This is probably due to a more favourable working environment for women. This is also very consistent with theoretical predictions by Akerlof and Kranton (2000 and 2010) who argue that the men hostility and distaste for women is higher in traditional industries which are predominantly “men’s jobs”.

Our results may have important implications for firms and HR managers. Diversity, opposite to an increasingly widespread belief, is not always positive. Moreover, the effect changes according to the firm environment: firms in more innovative sectors are likely to benefit from diversity while other not. High-tech/knowledge intensive sectors therefore can provide a good benchmark to more traditional industries to make also gender diversity functioning. Finally, the estimates show that the potential positive or negative effect is not negligible and a good workforce composition can significantly enhance firm's productivity. Future research on European countries should consider extending the diversity dimension to take into account also ethnic characteristics (or since in the EU for historic reasons it is quite difficult to have data on race at least the nationality) which is of increasing relevance in all developed countries.

[29] Concerning gender diversity, this paper mainly look at men dominated sectors because of the data availability (e.g. there is no public sector) and therefore gender diversity is measured mainly as a women intrusion in men dominated jobs and not the reverse.

References

Akerlof, G. and R. Kranton (2000), "Economics and Identity", *The Quarterly Journal of Economics*, vol. 115(3), pp.715-753.

Akerlof, G. and R. Kranton (2010), *Identity Economics*, Princeton University Press.

Alesina, A. and E. La Ferrara (2005), "Ethnic Diversity and Economic Performance", *Journal of Economic Literature*, vol. 43(3), pp. 762-800.

Arellano, M. and Bond, S. (1991), "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations", *Review of Economic Studies*, Vol. 58 No. 2, pp. 277-297.

Arellano, M. and Bover, O. (1995), "Another look at the instrumental variable estimation of error-components models", *Journal of Econometrics*, Vol. 68, pp 29-51.

Arun, S. and T. Arun (2002), "ICTs, gender and development: women in software production in Kerala", *Journal of International Development,* Vol. 14, pp. 39-50.

Barrington L. and K.R. Troske (2001), "Workforce Diversity and Productivity: An Analysis of Employer-Employee Match Data", Economics Program Working Papers 01-02, The Conference Board, Economics Program.

Becker, G. (1957), *The economics of discrimination*, The University of Chicago Press.

Bertrand, M., S. Black, S. Jensen and A. Lleras-Muney (2012), "Breaking the glass ceiling: the effect of board quotas on female labor market outcomes in Norway", mimeo.

Bloom, N. and J. Van Reenen (2011), "Human Resource Management and Productivity" in O. Ashenfelter and D. Card, *Handbook of Labor Economics*, Vol. 1B.

Blundell, R. and S. Bond (1998), "Initial conditions and moment restrictions in dynamic panel data models", *Journal of Econometrics*, 87, pp 115-143.

Cataldi, A. S. Kampelmann and F. Rycx (2011), "Productivity-Wage Gaps Among Age Groups: Does the ICT Environment Matter?", *De Economist* (*Netherlands Economic Review*), Vol. 159, No. 2, pp. 193-221.

Cataldi, A., S. Kampelmann and F. Rycx (2012), "Part-time Work, Wages, and Productivity: Evidence from Matched Panel Data", mimeo.

Chattopadhyay, P. (1999), "Beyond direct and symmetrical effects: the influence of demographic dissimilarity on organizational citizenship behaviour", *Academy of Management Journal*, Vol. 42, pp. 273-287.

Choi, J.N. (2007), "Group composition and employee creative behaviour in a Korean electronics company: Distinct effects of relational demography and group diversity", *Journal of Occupational and Organizational Psychology*, Vol. 80, pp. 213-234.

Cook, A. and C. Glass (2011), "Does diversity damage corporate value? Measuring stock price reactions to a diversity award", *Ethnic and Racial Studies*, Vol. 34, pp. 2173-2191.

Cox, T. (1993), *Cultural Diversity in Organizations: Theory, Research, and Practice*, Berrett-Koehler.

Cummings, J. N. (2004), "Work groups, structural diversity, and knowledge sharing in a global organization", *Management Science*, 50(3), 352-364.

Demunter, C. (2000), "Structure and distribution of earnings survey: Analysis 1995", Statistics Belgium Working paper, Brussels.

Dostie, B. (2011), "Wages, productivity and aging", *De Economist*, Vol. 159, pp. 139-158.

Göbel, C. and T. Zwick (2012), "Age and Productivity – Sector Differences", *De Economist* 160 (1), pp. 35-57.

Greif, A. (1993), "Contract Enforceability and Economic Institutions in Early Trade: The Maghribi Traders' Coalition", *American Economic Review*, 83(3), 525-548.

Grund, C. and N. Westergaard-Nielsen (2008), "Age structure of the workforce and firm performance", *International Journal of Manpower*, vol. 29(5), pages 410-422.

Haile, G. (2012), "Unhappy working with men? Workplace gender diversity and employee Job-related well-being in Britain: a WERS2004 based analysis", *Labour Economics*, pp. 329-350.

Hamilton, B., J. Nickerson and H. Owan (2004), "Diversity and Productivity in Production Teams", Olin Business School WP.

Harrison, D. and K. Klein (2007), "What's the difference? Diversity, constructs as separation, variety or disparity in organizations", *Academy of Management Review*, Vol. 32, No. 4, pp. 1199-1228.

Hellerstein and Neumark (1995), "Are earnings profiles steeper than productivity profiles? Evidence from Israeli firm data", Vol. 30 No. 1, *Journal of Human Resources*, pp. 89-112.

Hellerstein, J. and D. Neumark (2004), "Production function and wage equation estimation with heterogeneous labor: Evidence from a new matched employer-employee data set", NBER Working Paper no. 10365, Cambridge, MA.

Hellerstein, J., D. Neumark and K. Troske (1999), "Wages, productivity, and worker characteristics: Evidence from plant-level production functions and wage equations", *Journal of Labor Economics*, Vol. 17, pp. 409-446.

Herring, C. (2009), "Does Diversity Pay?: Race, Gender, and the Business Case for Diversity", American Sociological Review, Vol. 74, pp. 208-224.

Hoogendoorn, S. and M. Van Praag (2011), "Ethnic diversity and team performance: a randomized field experiment, IZA Discussion Paper No. 6731.

Hoogendoorn, S., H. Oosterbeek and M. Van Praag (2011), "The impact of gender diversity on the performance of business teams: Evidence from a field experiment", Tinbergen Institute Discussion Papers 11-074/3.

Horwitz, S.K. and I.B. Horwitz (2007), "The effects of team diversity on team outcomes: A meta-analytic review of team demography", *Journal of Management*, 33, pp. 987-1015.

Ilmakunnas, P. and S. Ilmakunnas (2011), "Diversity at the Workplace: Whom Does it Benefit?", *De Economist*, Vol. 159, No. 2, pp. 223-255.

Iranzo, S., F. Schivardi and E. Tosetti (2008), "Skill Dispersion and Firm Productivity: An Analysis with Employer-Employee Matched Data", *Journal of Labor Economics*, vol. 26(2), pp. 247-285, 04.

Jackson, S.E., A. Joshi and N. Erhardt (2003), "Recent research on team and organizational diversity: SWOT analysis and implications", *Journal of Management*, Vol. 29, pp. 801-830.

Kahane, L., N. Longley and R. Simmons (2012), "The Effects of Coworker Heterogeneity on Firm-Level Output: Assessing the Impacts of Cultural and Language Diversity in the National Hockey League", *Review of Economics and Statistics*, forthcoming.

Kampelmann, S. and F. Rycx (2012), "Are occupations paid what they are worth? An econometric study of occupational wage inequality and productivity", *De Economist*, forthcoming.

Kremer, M. (1994), "The O-Ring theory of economic development", *Quarterly Journal of Economics* 108 (1993), pp.551-575.

Kristof, A. (1996), "Person-organization fit: an integrative review of its conceptualizations, measurement, and implications", *Personnel Psychology*, Vol. 49, Issue 1, pp. 1–49.

Kurtulus, F.A. (2011), "What Types of Diversity Benefit Workers? Empirical Evidence on the Effects of Co-Worker Dissimilarity on the Performance of Employees", *Industrial Relations: A Journal of Economy and Society*, Vol. 50, Issue 4, pp. 678-712.

Lazear, E. (1999), "Globalisation and the Market for Team-Mates", *Economic Journal*, vol. 109(454), pages C15-40.

Lee, C. and J. Farh (2004), "Joint effects of group efficacy and gender diversity on group cohesion and performance", *Applied Psychology*: *An International Review*, 53(1), pp. 136-154.

Leonard, J. and D. Levine (2006), "Diversity, Discrimination, and Performance", Institute for Research on Labor and Employment, Working Paper Series 304497, Institute of Industrial Relations, UC Berkeley.

Levinsohn, J. and A. Petrin (2003), "Estimating Production Functions Using Inputs to Control for Unobservables", *Review of Economic Studies*, vol. 70(2), pages 317-341, 04.

Mas, A. and Moretti, E. (2009), "Peers at Work", *American Economic Review*, Vol. 99, pp. 112-145.

Navon, G. (2009), "Human Capital Spillovers in the Workplace: Labor Diversity and Productivity", MPRA Paper 17741, University Library of Munich, Germany.

OECD (2009), *Measuring Capital*, OECD Publishing, Paris.

Olley, G. S. and A. Pakes (1996), "The dynamics of productivity in the telecommunications equipment industry", *Econometrica*, 64(6): 1263-1297.

O'Mahony, M. and van Ark, B. (2003), "EU productivity and competitiveness: An industry perspective. Can Europe resume the catching-up process?", Luxembourg: European Commission.

Osborne, E. (2000), "The Deceptively Simple Economics of Workplace Diversity", *Journal of Labor Research*, 21 (2000), 463-475.

Parrotta, P. D. Pozzoli and M. Pytlikova (2010a), "Does Labor Diversity Affect Firm Productivity?", Aarhus School of Business, Department of Economics, WP 10-12.

Parrotta, P. D. Pozzoli and M. Pytlikova (2010b), "The Nexus between Labor Diversity and Firm´s Innovation", Working Papers 10-15, University of Aarhus, Aarhus School of Business, Department of Economics.

Prat, A. (2002), "Should a team be homogeneous?", *European Economic Review*, 46 (7), pp. 1187-1207.

Pull, K., B. Pferdmenges and U. Backes-Gellner (2012), "Knowledge Production Process, Diversity Type and Group Interaction as Moderators of the Diversity-Performance-Link: An Analysis of University Research Groups", Working Papers 0158, University of Zurich, Institute for Strategy and Business Economics (ISU).

Roberge, M-E. and R. van Dick (2010), "Recognizing the benefits of diversity: When and how diversity increase group performance?", *Human Resource Management Review*, 20, pp. 295-308.

Sen, S. and C. Bhattacharya (2011), "Does Doing Good Always Lead to Doing Better? Consumer Reactions to Corporate Social Responsibility", *Journal of Marketing Research*, Vol. 38, pp. 225-243.

van Ours, J. and Stoeldraijer, L. (2011), "Age, wage and productivity in Dutch manufacturing", *De Economist*, vol. 159, pp. 113-137.

Vandenberghe, V. (2011), "Firm-level Evidence on Gender Wage Discrimination", *Labour: Review of Labour Economics and Industrial Relations*, 25(3), pp. 330-349.

Vandenberghe, V. (2012), "Are firms willing to employ a greying and feminizing workforce?", *Labour Economics*, forthcoming.

Webster, J. (2007), "Diversity Management in the ICT Industry. Challenges and Issues for Social Dialogue", Report prepared for Union Network International.

Wooldridge, J. (2002), *Econometric Analysis of Cross Section and Panel Data*, MIT Press.

Table 1 : Empirical studies on workforce diversity and firm performance.

	Study	Country (data coverage)	Firm/Sector	Performance indicator	Charact. Considered	Diversity index	Estimation technique	Results
One company	Choi (2007)	Korea	Electronic	Employees' creative behaviour	Age, gender, tenure, hierarchical status, performance, function	Dissimilarity and entropy	OLS	Gender and hierarchical status and performance level negative. Age and performance level and group diversity in functional background positive.
	Cummings (2004)	Multinational	Telecommunications	Management rating of group performance	Demographic, structural (geo. location, functional assignment) and knowledge sharing	Std. Dev. for demographics, entropy for structural diversity	Ordered Logit	Knowledge sharing more valuable when groups are more structurally diverse
	Hamilton et al. (2004)	USA (1995-1997)	Garment manufacturing	Piece rate production (at individal and team level)	Worker abilities, age, ethnicity	Ability: ratio of the maximum to the minimum average individual productivity levels of the team members. Age: std.dev.. Ethnicity: % of Hispanic	OLS/Median/FE	Ability: positive effect. Age: negative. Ethnicity: positive. (but for age and ethnicity not robust)
	Kurtulus (2011)	Multinational (1989-1994)	Health services	Worker performance evaluation	Demographic (age, race, gender) and non demographic (education, work function, firm tenure, division tenure, performance and wages)	Dissimilarity	OLS/FE	Age, firm tenure and performance: negative effect. Wage: positive effect.
	Leonard and Levine (2006)	USA (1996-1998, monthly)	Large retail firm	Monthly sales	Age, race, gender	Gender and race: Herfindahl. Age: std. Dev.	OLS/FD	Age: negative. Race and gender: not significant.
LEED	Barrington and Troske (2001)	USA (1990)	Manufacturing, retail trade and services	Value-added and total sales per capita	Payroll and occupation	Unique index	OLS	No significant relationship

	Grund and Westergaard-Nielsen (2008)	Denmark (1992-1997)	All	Value-added per capita	Age structure (mean and dispersion)	Std. Dev.	OLS/FE	U-shaped relation with firm performance
	Ilmakunnas and Ilmakunnas (2011)	Finland (1995-2004)	All	TFP (+ wages for workers)	Age, education	Std. dev., dissimilarity, variety (Blau) and two dimensional age-education index	OLS/FE/GMM/OP	Age positive on TFP and wage and education negative on TFP.
	Navon (2009)	Israel (2000-2003)	Manufacturing	Value-added	Knowledge (type of degree)	Herfindahl	OLS/LP/OP	Positive effect of knowledge diversity
	Parrotta et al. (2010)	Denmark (from 1994 for construction, 1995 for manufacturing, 1998 for wholesale trade, 1999 for services to 2005)	All	TFP (estimated with Wooldridge (2009) approach)	Cultural background, skills/education and demographics	Herfindahl	OLS/IV	Positive for skills/education; mixed (depending on the specification) for demographics and ethnicity
Others	Cook and Glass (2011)	USA (2001-2003)	Fortune's magazine 50 Best Companies for Minorities	Stock prices	Ethnic minorities	% of minorities	OLS	Negative results on share price
	Herring (2012)	USA (1996-1997)	All (National Organizations Survey)	Annual sales revenues	Race, gender	Dissimilarity index and asymmetrical index	OLS	Positive effects
	Hoogendoorn et al. (2011)	Denmark 2008-2009	Field experiment in a business school	Simulated sales, profits and profits per share in teams.	Gender	Women share and gender diversity index	OLS	Teams with an equal gender mix perform better than male-dominated and female-dominated teams

	Hoogendoorn and Van Praag (2012)	Denmark 2008-2009	Field experiment in a business school	Simulated sales, profits and profits per share in teams.	Ethnicity	Share of minorities	OLS	A moderate level of ethnic diversity has no effect. However, if at least the majority of team members is ethnically diverse, then more ethnic diversity has a positive impact.
	Kahane et al.	USA (2001-2008 except season 2004-05)	National Hockey League	Team level (nb of matches won, points and goals difference); individual level (points, goals, assists)	Country of birth	Herfindahl	FE	Teams with higher % of European players perform better, but if the players come from the same country rather than many.

Table 2: Descriptive statistics (1999-2006)

	All		HT/KIS		Non-HT/KIS	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Hourly wage (2006 euros)	17.14	5.39	18.38	5.68	16.64	5.18
Value-added per hour (2006 euros)	61.06	458.61	64.49	239.10	59.71	520.20
Capital	244,287	2,117,000	489,790	3,946,000	147,644	292,979
Investment	18,543	254,447	40,205	476,648	10,019	24,221
Firm size	268.30	281.99	299.90	326.80	255.90	261.20
Average workers age	38.42	4.19	37.45	4.35	38.80	4.07
Age std. dev. intra firms	9.33	1.82	9.01	2.01	9.45	1.73
Age dissimilarity index intra firms	12.61	2.52	12.16	2.77	12.79	2.39
Women	0.27	0.24	0.33	0.25	0.24	0.23
Gender std. Dev.	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
Year of education	11.44	1.76	12.32	1.79	11.09	1.62
Education std. dev. intra firms	1.90	0.84	1.79	0.77	1.94	0.86
Education dissimilarity index intra firms	2.54	1.15	2.40	1.05	2.60	1.18
White collar (manager, professionals, technicians, clerks and service)	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
Non standard (i.e. non open-ended) employment contract	0.04	0.10	0.05	0.12	0.04	0.09
Worker tenure:						
<= 1 year	0.20	0.16	0.23	0.18	0.19	0.16
2-4 years	0.21	0.15	0.24	0.17	0.20	0.14
5-9 years	0.20	0.14	0.21	0.16	0.19	0.14
>= 10 years	0.39	0.24	0.33	0.25	0.42	0.24
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 (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
Number of observations	7463		2108		5355	
Number of firms	2431		679		1778	

Notes: Count of HT/KIS and non-HT/KIS firms exceeds the number of all firms due to firms that changed category during the observation period. Monetary values in 2006 euros.

Table 3: Baseline estimates with standard deviation (pooled OLS, GMM and LP approach, 1999-2006).

	OLS			GMM			LP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Value-added	Wage	Diff. VA-WG	Value-added	Wage	Diff. VA-WG	Value-added
Age std. dev	-0.009*	-0.010***	0.001	-0.022***	-0.010***	-0.013*	-0.007**
	(0.005)	(0.002)	(0.005)	(0.008)	(0.004)	(0.007)	(0.003)
Education std. dev	0.037***	0.034***	0.003	0.009	0.017**	-0.008	0.032***
	(0.010)	(0.004)	(0.008)	(0.015)	(0.007)	(0.013)	(0.008)
Gender std. dev	-0.089	-0.163***	0.074	-0.260**	-0.140**	-0.120	-0.113*
	(0.064)	(0.027)	(0.055)	(0.102)	(0.055)	(0.094)	(0.064)
Age average	0.013***	0.013***	-0.000	0.011***	0.009***	0.002	0.010***
	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.002)
Education average	0.096***	0.062***	0.034***	0.077***	0.046***	0.032***	0.075***
	(0.007)	(0.003)	(0.005)	(0.007)	(0.003)	(0.006)	(0.006)
Observations	7463	7463	7463	7463	7463	7463	7461
Number of firms	2431	2431	2431	2431	2431	2431	2431
R-squared	0.245	0.407	0.112				
P-value Hansen test				0.765	0.152	0.487	
P-value AR(2)				0.123	0.370	0.560	

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Regressions include worker and firm characteristics (% non open-ended, % part-time, firm size, % workers with >10 years of tenure, % white collars, capital stock), industry (8 dummies) and time dummies (7). In GMM first and second lags of explanatory variables are used as instruments.

Table 4: Baseline estimates with dissimilarity index (pooled OLS, GMM and LP approach, 1999-2006).

	OLS			GMM			LP
	(1) Value-added	(2) Wage	(3) Diff. VA-WG	(4) Value-added	(5) Wage	(6) Diff. VA-WG	(7) Value-added
Age dissimilarity	-0.007*	-0.007***	0.000	-0.016***	-0.007***	-0.009*	-0.005*
	(0.004)	(0.001)	(0.003)	(0.006)	(0.003)	(0.005)	(0.003)
Education dissimilarity	0.028***	0.025***	0.003	0.007	0.012**	-0.005	0.024***
	(0.007)	(0.003)	(0.006)	(0.011)	(0.005)	(0.010)	(0.006)
Gender dissimilarity	-0.058	-0.115***	0.058	-0.176**	-0.097**	-0.079	-0.075*
	(0.046)	(0.019)	(0.040)	(0.076)	(0.041)	(0.069)	(0.039)
Age average	0.013***	0.013***	-0.000	0.011***	0.009***	0.002	0.010***
	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.002)
Education average	0.096***	0.062***	0.034***	0.077***	0.046***	0.032***	0.075***
	(0.007)	(0.003)	(0.005)	(0.007)	(0.003)	(0.006)	(0.005)
Observations	7463	7463	7463	7463	7463	7463	7461
Number of firms	2431	2431	2431	2431	2431	2431	2431
R-squared	0.245	0.407	0.112				
P-value Hansen test				0.767	0.172	0.480	
P-value AR(2)				0.124	0.356	0.561	

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Regressions include worker and firm characteristics (% non open-ended, % part-time, firm size, % workers with >10 years of tenure, % white collars, capital stock), industry (8 dummies) and time dummies (7). In GMM first and second lags of explanatory variables are used as instruments.

Table 5: HT/KIS estimates with standard deviation (pooled OLS, GMM and LP approach, 1999-2006).

	OLS			GMM			LP
	(1) Value-added	(2) Wage	(3) Diff. VA-WG	(4) Value-added	(5) Wage	(6) Diff. VA-WG	(7) Value-added
Age std. dev	-0.004	-0.005**	0.001	-0.022**	-0.011**	-0.011	-0.001
	(0.006)	(0.002)	(0.006)	(0.010)	(0.005)	(0.009)	(0.005)
Education std. dev	0.029***	0.034***	-0.004	0.011	0.001	0.010	0.025***
	(0.010)	(0.005)	(0.009)	(0.022)	(0.010)	(0.021)	(0.009)
Gender std. dev	-0.198***	-0.206***	0.008	-0.327**	-0.172**	-0.155	-0.194***
	(0.072)	(0.032)	(0.061)	(0.136)	(0.068)	(0.123)	(0.069)
Age std. dev*HT/KIS	-0.012	-0.009**	-0.003	0.011	0.006	0.005	-0.014
	(0.011)	(0.004)	(0.009)	(0.026)	(0.012)	(0.024)	(0.009)
Education std. dev*HT/KIS	0.032	0.002	0.030	-0.007	0.039*	-0.047	0.033
	(0.026)	(0.010)	(0.023)	(0.056)	(0.022)	(0.049)	(0.024)
Gender std. Dev*HT/KIS	0.416***	0.196***	0.219*	0.716*	0.174	0.542	0.343**
	(0.150)	(0.054)	(0.132)	(0.398)	(0.139)	(0.361)	(0.147)
Age average	0.013***	0.013***	-0.000	-0.005	0.003	-0.008	0.008***
	(0.004)	(0.001)	(0.004)	(0.016)	(0.008)	(0.014)	(0.003)
Education average	0.091***	0.050***	0.041***	0.055	0.002	0.053	0.063***
	(0.008)	(0.003)	(0.007)	(0.043)	(0.020)	(0.040)	(0.005)
Age average*HT/KIS	0.001	0.003	-0.002	0.035*	-0.001	0.036**	0.006
	(0.006)	(0.002)	(0.006)	(0.021)	(0.010)	(0.018)	(0.004)
Education average*HT/KIS	0.022	0.038***	-0.016	0.066	0.064**	0.002	0.037***
	(0.015)	(0.006)	(0.013)	(0.064)	(0.029)	(0.053)	(0.010)
HT/KIS	-0.444	-0.525***	0.081	-2.552***	-0.934**	-1.618*	-0.691***
	(0.339)	(0.119)	(0.294)	(0.981)	(0.453)	(0.868)	(0.213)
Observations	7463	7463	7463	7463	7463	7463	7461
Number of firms	2431	2431	2431	2431	2431	2431	2431
R-squared	0.251	0.423	0.118				
P-value Hansen test				0.177	0.0551	0.334	
P-value AR(2)				0.117	0.458	0.499	

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Regressions include worker and firm characteristics (% non open-ended, % part-time, firm size, % workers with >10 years of tenure, % white collars, capital stock), industry (8 dummies) and time dummies (7). In GMM first and second lags of explanatory variables are used as instruments.

Table 6: HT/KIS estimates with dissimilarity index (pooled OLS, GMM and LP approach, 1999-2006).

	OLS			GMM			LP
	(1) Value-added	(2) Wage	(3) Diff. VA-WG	(4) Value-added	(5) Wage	(6) Diff. VA-WG	(7) Value-added
Age dissimilarity	-0.003	-0.004**	0.001	-0.017**	-0.007**	-0.009	-0.001
	(0.005)	(0.002)	(0.004)	(0.007)	(0.003)	(0.007)	(0.003)
Education dissimilarity	0.023***	0.025***	-0.002	0.006	0.001	0.005	0.019***
	(0.008)	(0.003)	(0.006)	(0.016)	(0.007)	(0.015)	(0.007)
Gender dissimilarity	-0.145***	-0.150***	0.005	-0.230**	-0.119**	-0.112	-0.142***
	(0.053)	(0.023)	(0.045)	(0.100)	(0.050)	(0.089)	(0.039)
Age dissimilarity*HT/KIS	-0.009	-0.007**	-0.002	0.011	0.004	0.007	-0.010
	(0.008)	(0.003)	(0.007)	(0.019)	(0.009)	(0.017)	(0.007)
Education dissimilarity*HT/KIS	0.023	0.002	0.021	-0.001	0.026	-0.028	0.023
	(0.019)	(0.007)	(0.016)	(0.040)	(0.016)	(0.034)	(0.017)
Gender dissimilarity*HT/KIS	0.318***	0.149***	0.169*	0.527*	0.121	0.406	0.261***
	(0.107)	(0.039)	(0.093)	(0.283)	(0.102)	(0.255)	(0.091)
Age average	0.013***	0.013***	-0.000	-0.003	0.003	-0.006	0.008***
	(0.004)	(0.001)	(0.004)	(0.016)	(0.008)	(0.014)	(0.003)
Education average	0.091***	0.050***	0.041***	0.048	0.002	0.046	0.064***
	(0.008)	(0.003)	(0.007)	(0.042)	(0.019)	(0.039)	(0.007)
Age average*HT/KIS	0.001	0.003	-0.002	0.034	-0.000	0.034*	0.006
	(0.006)	(0.002)	(0.006)	(0.021)	(0.010)	(0.018)	(0.004)
Education average*HT/KIS	0.021	0.038***	-0.016	0.073	0.062**	0.011	0.037***
	(0.015)	(0.006)	(0.013)	(0.064)	(0.029)	(0.052)	(0.013)
HT/KIS	-0.441	-0.526***	0.085	-2.635***	-0.896**	-1.739**	-0.689***
	(0.338)	(0.118)	(0.293)	(0.972)	(0.452)	(0.860)	(0.212)
Observations	7463	7463	7463	7463	7463	7463	7461
Number of firms	2431	2431	2431	2431	2431	2431	2431
R-squared	0.252	0.424	0.118				
P-value Hansen test				0.192	0.0647	0.306	
P-value AR(2)				0.116	0.442	0.502	

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Regressions include worker and firm characteristics (% non open-ended, % part-time, firm size, % workers with >10 years of tenure, % white collars, capital stock), industry (8 dummies) and time dummies (7). In GMM first and second lags of explanatory variables are used as instruments.

Appendix A: Further results

Table A.1: Baseline estimates with gender diversity index (GMM and LP, 1999-2006)

Panel A

	GMM			LP
	(1)	(2)	(3)	(4)
	Value-added	Wage	Diff. VA-WG	Value-added
Age std. dev	-0.022***	-0.009***	-0.013*	-0.007
	(0.008)	(0.004)	(0.007)	(0.005)
Education std. dev	0.008	0.016**	-0.008	0.031***
	(0.015)	(0.007)	(0.013)	(0.010)
Gender diversity index	-0.390*	-0.234**	-0.156	-0.160
	(0.229)	(0.115)	(0.197)	(0.109)
Age average	0.011***	0.009***	0.002	0.010***
	(0.004)	(0.001)	(0.003)	(0.002)
Education average	0.077***	0.046***	0.031***	0.075***
	(0.007)	(0.003)	(0.006)	(0.007)
Observations	7463	7463	7463	7461
Number of firms	2431	2431	2431	2431
P-value Hansen test	0.866	0.117	0.468	
P-value AR(2)	0.131	0.349	0.564	

Panel B

	GMM			LP
	(1)	(2)	(3)	(4)
	Value-added	Wage	Diff. VA-WG	Value-added
Age dissimilarity	-0.016***	-0.007***	-0.009*	-0.005*
	(0.006)	(0.003)	(0.005)	(0.003)
Education dissimilarity	0.006	0.012**	-0.005	0.023***
	(0.011)	(0.005)	(0.010)	(0.006)
Gender diversity index	-0.389*	-0.230**	-0.159	-0.162*
	(0.229)	(0.116)	(0.197)	(0.090)
Age average	0.011***	0.009***	0.002	0.010***
	(0.004)	(0.001)	(0.003)	(0.003)
Education average	0.077***	0.046***	0.031***	0.075***
	(0.007)	(0.003)	(0.006)	(0.007)
Observations	7463	7463	7463	7461
Number of firms	2431	2431	2431	2431
P-value Hansen test	0.840	0.140	0.461	
P-value AR(2)	0.130	0.343	0.564	

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Regressions include worker and firm characteristics (% non open-ended, % part-time, firm size, % workers with >10 years of tenure, % white collars, capital stock), industry (8 dummies) and time dummies (7). In GMM first and second lags of explanatory variables are used as instruments.

Table A.2: Estimates for non-linearities (GMM, 1999-2006).

	(1) Value-added	(2) Wage	(3) Diff. VA-WG	(4) Value-added	(5) Wage	(6) Diff. VA-WG	(7) Value-added	(8) Wage	(9) Diff. VA-WG
Age std. Dev	-0.022*	-0.005	-0.017	-0.023**	-0.009*	-0.014	-0.046***	-0.009	-0.037**
	(0.013)	(0.006)	(0.011)	(0.011)	(0.005)	(0.010)	(0.017)	(0.007)	(0.015)
Education std. Dev	0.032	0.003	0.028	-0.010	0.013	-0.023	-0.035	-0.010	-0.024
	(0.020)	(0.010)	(0.018)	(0.016)	(0.009)	(0.015)	(0.031)	(0.014)	(0.030)
Gender std. Dev	-0.233**	-0.145**	-0.088	-0.278***	-0.180***	-0.098	-0.387***	-0.203***	-0.185
	(0.109)	(0.060)	(0.101)	(0.099)	(0.057)	(0.091)	(0.123)	(0.068)	(0.113)
Age std. Dev*p33	0.001	-0.002	0.003				0.010***	-0.001	0.010***
	(0.003)	(0.001)	(0.002)				(0.003)	(0.002)	(0.003)
Education std. Dev*p33	-0.012	0.011*	-0.022**				0.017	0.015*	0.001
	(0.012)	(0.006)	(0.010)				(0.021)	(0.009)	(0.020)
Gender std. Dev*p33	0.004	-0.012	0.016				0.147*	0.014	0.132**
	(0.060)	(0.034)	(0.052)				(0.075)	(0.041)	(0.066)
Age std. Dev*p66				0.001	-0.001	0.001	0.012**	-0.001	0.013***
				(0.002)	(0.001)	(0.002)	(0.005)	(0.002)	(0.005)
Education std. Dev*p66				0.015	0.006	0.009	0.033	0.023**	0.010
				(0.009)	(0.005)	(0.009)	(0.025)	(0.011)	(0.023)
Gender std. Dev*p66				0.018	0.034	-0.016	0.163	0.057	0.106
				(0.066)	(0.031)	(0.055)	(0.105)	(0.052)	(0.088)
Age average	0.011***	0.009***	0.002	0.011***	0.009***	0.001	0.011***	0.010***	0.002
	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)
Education average	0.078***	0.047***	0.031***	0.079***	0.047***	0.032***	0.080***	0.048***	0.032***
	(0.007)	(0.004)	(0.006)	(0.008)	(0.003)	(0.006)	(0.007)	(0.004)	(0.006)
Observations	7463	7463	7463	7463	7463	7463	7463	7463	7463
Number of firms	2431	2431	2431	2431	2431	2431	2431	2431	2431
P-value Hansen test	0.735	0.0694	0.809	0.669	0.339	0.413	0.711	0.176	0.685
P-value AR(2)	0.125	0.339	0.588	0.123	0.355	0.565	0.107	0.374	0.595

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. First and second lags of explanatory variables are used as instruments.

Table A.3: Estimates using KIA taxonomy (Pooled OLS, GMM and LP estimates)

	OLS			GMM			LP
	(1) Value-added	(2) Wage	(3) Diff. VA-WG	(4) Value-added	(5) Wage	(6) Diff. VA-WG	(7) Value-added
Age std. dev	-0.007	-0.006***	-0.001	-0.020**	-0.004	-0.016**	-0.005
	(0.005)	(0.002)	(0.004)	(0.008)	(0.004)	(0.007)	(0.004)
Education std. dev	0.026***	0.033***	-0.007	0.017	0.013*	0.005	0.024***
	(0.010)	(0.005)	(0.009)	(0.015)	(0.007)	(0.014)	(0.009)
Gender std. dev	-0.111*	-0.167***	0.056	-0.329***	-0.080	-0.249**	-0.137**
	(0.066)	(0.028)	(0.057)	(0.107)	(0.055)	(0.103)	(0.069)
Age std. Dev*KIA	-0.012	-0.009	-0.003	-0.000	-0.018*	0.018	-0.005
	(0.018)	(0.005)	(0.017)	(0.027)	(0.010)	(0.023)	(0.012)
Education std.	0.050*	0.003	0.047**	-0.021	0.017	-0.038	0.039
dev*KIA	(0.028)	(0.012)	(0.024)	(0.042)	(0.020)	(0.034)	(0.024)
Gender std. Dev*KIA	0.139	0.028	0.111	0.696**	0.025	0.671**	0.133
	(0.232)	(0.074)	(0.215)	(0.330)	(0.140)	(0.288)	(0.148)
Age average	0.002	0.011***	-0.008***	0.002	0.008***	-0.006*	0.004*
	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)
Education average	0.078***	0.048***	0.030***	0.063***	0.031***	0.031***	0.059***
	(0.007)	(0.003)	(0.006)	(0.008)	(0.004)	(0.007)	(0.006)
Age average*KIA	0.042***	0.010***	0.031**	0.031***	0.007**	0.024***	0.024***
	(0.012)	(0.002)	(0.013)	(0.008)	(0.003)	(0.007)	(0.005)
Education	0.054***	0.040***	0.014	0.037**	0.038***	-0.001	0.051***
average*KIA	(0.016)	(0.006)	(0.014)	(0.014)	(0.007)	(0.012)	(0.010)
KIA	-2.167***	-0.714***	-1.453***	-1.605***	-0.448***	-1.156***	-1.459***
	(0.522)	(0.135)	(0.517)	(0.340)	(0.159)	(0.301)	(0.211)
Observations	7463	7463	7463	7463	7463	7463	7461
Number of firms	2431	2431	2431	2431	2431	2431	2431
R-squared	0.271	0.434	0.130				
P-value Hansen test				0.639	0.000748	0.674	
P-value AR(2)				0.161	0.375	0.590	

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Regressions include worker and firm characteristics (% non open-ended, % part-time, firm size, % workers with >10 years of tenure, % white collars, capital stock), industry (8 dummies) and time dummies (7). In GMM first and second lags of explanatory variables are used as instruments.

Table A.4: Estimates using ICT taxonomy (Pooled OLS, GMM and LP estimates)

	OLS			GMM			LP
	(1) VA h OLS	(2) W hour OLS	(3) Diff OLS	(4) Value-added	(5) Wage	(6) Diff. VA-WG	(7) Value-added
Age std. Dev	-0.007	-0.009***	0.003	-0.039***	-0.013***	-0.026***	-0.003
	(0.007)	(0.002)	(0.006)	(0.011)	(0.005)	(0.009)	(0.006)
Education std. Dev	0.041***	0.040***	0.001	0.008	0.017**	-0.008	0.033***
	(0.011)	(0.005)	(0.009)	(0.016)	(0.008)	(0.015)	(0.010)
Gender std. Dev	-0.197**	-0.237***	0.039	-0.362***	-0.186***	-0.176	-0.208***
	(0.080)	(0.032)	(0.069)	(0.124)	(0.065)	(0.114)	(0.069)
Age std. Dev * ICT	-0.002	-0.000	-0.002	0.051**	0.012	0.040**	-0.005
	(0.010)	(0.004)	(0.009)	(0.024)	(0.011)	(0.020)	(0.008)
Education std. Dev *	-0.012	-0.019**	0.007	0.017	0.008	0.009	0.000
ICT	(0.022)	(0.009)	(0.019)	(0.037)	(0.018)	(0.032)	(0.019)
Gender std. Dev * ICT	0.437***	0.276***	0.160	0.533**	0.237*	0.295	0.366***
	(0.134)	(0.056)	(0.118)	(0.265)	(0.138)	(0.233)	(0.118)
Age average	0.017***	0.012***	0.005	0.019***	0.010***	0.009***	0.010***
	(0.005)	(0.001)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)
Education average	0.089***	0.052***	0.037***	0.067***	0.036***	0.031***	0.060***
	(0.009)	(0.003)	(0.008)	(0.008)	(0.004)	(0.007)	(0.006)
Age average * ICT	-0.010	0.003*	-0.014**	-0.025***	-0.002	-0.023***	-0.002
	(0.006)	(0.002)	(0.006)	(0.007)	(0.003)	(0.005)	(0.004)
Education average * ICT	0.024*	0.029***	-0.005	0.036**	0.032***	0.004	0.042***
	(0.014)	(0.006)	(0.012)	(0.015)	(0.007)	(0.012)	(0.012)
ICT	-0.059	-0.539***	0.480*	-0.184	-0.481***	0.297	-0.482**
	(0.328)	(0.111)	(0.291)	(0.313)	(0.149)	(0.269)	(0.226)
Workers's and firms' characteristics	X	X	X	X	X	X	X
Industry and time dummies	X	X	X	X	X	X	X
Observations	7463	7463	7463	7463	7463	7463	7461
Number of random	2431	2431	2431	2431	2431	2431	2431
R-squared	0.253	0.421	0.118				
P-value Hansen test				0.553	0.0881	0.183	
P-value AR(2)				0.0625	0.336	0.509	

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Regressions include worker and firm characteristics (% non open-ended, % part-time, firm size, % workers with >10 years of tenure, % white collars, capital stock), industry (8 dummies) and time dummies (7). In GMM first and second lags of explanatory variables are used as instruments.

Table A.5: Estimates services vs. manufacturing (GMM and LP estimates, 1999-2006)

Panel A

	GMM			LP
	(1)	(2)	(3)	(4)
	Value added	Wage	Diff. VA-WG	VA
Age std. dev	-0.035***	-0.008	-0.027***	-0.002
	(0.011)	(0.006)	(0.010)	(0.004)
Education std. dev	-0.002	0.017*	-0.019	0.028***
	(0.021)	(0.009)	(0.019)	(0.010)
Gender std. dev	-0.392***	-0.155**	-0.237*	-0.184**
	(0.134)	(0.075)	(0.134)	(0.086)
Age std. Dev*Services	0.029	-0.006	0.035*	-0.009
	(0.021)	(0.012)	(0.019)	(0.007)
Education std. Dev*Services	0.026	0.002	0.024	0.008
	(0.029)	(0.015)	(0.026)	(0.017)
Gender std. Dev*Services	0.228	0.028	0.201	0.222*
	(0.205)	(0.123)	(0.200)	(0.121)
Age average	0.014***	0.011***	0.003	0.009***
	(0.004)	(0.002)	(0.004)	(0.004)
Education average	0.074***	0.040***	0.034***	0.071***
	(0.010)	(0.004)	(0.008)	(0.008)
Age average*Services	-0.009	-0.003	-0.005	0.002
	(0.006)	(0.003)	(0.006)	(0.004)
Education average*Services	0.011	0.013*	-0.002	0.008
	(0.014)	(0.007)	(0.011)	(0.010)
Services	-0.316	-0.052	-0.264	-0.267
	(0.274)	(0.146)	(0.236)	(0.238)
Observations	7463	7463	7463	7461
Number of firms	2431	2431	2431	2431
P-value Hansen test	0.704	0.00207	0.855	
P-value AR(2)	0.155	0.384	0.719	

Panel B

	GMM			LP
	(1)	(2)	(3)	(4)
	Value added	Wage	Diff. VA-WG	Value added
Age dissimilarity	-0.026***	-0.006	-0.020***	-0.002
	(0.008)	(0.004)	(0.007)	(0.004)
Education dissimilarity	-0.000	0.012*	-0.012	0.022***
	(0.015)	(0.007)	(0.014)	(0.008)
Gender dissimilarity	-0.273***	-0.112**	-0.162*	-0.134***
	(0.097)	(0.054)	(0.096)	(0.051)
Age dissimilarity*Services	0.022	-0.003	0.025*	-0.007
	(0.015)	(0.009)	(0.014)	(0.005)
Education dissimilarity*Services	0.017	0.001	0.015	0.005
	(0.021)	(0.011)	(0.019)	(0.013)
Gender dissimilarity*Services	0.164	0.023	0.140	0.184**
	(0.153)	(0.091)	(0.146)	(0.086)
Age average	0.014***	0.011***	0.003	0.009***
	(0.004)	(0.002)	(0.004)	(0.003)
Education average	0.074***	0.040***	0.034***	0.071***
	(0.010)	(0.004)	(0.008)	(0.006)
Age average*Services	-0.009	-0.003	-0.005	0.002
	(0.006)	(0.003)	(0.005)	(0.004)
Education average*Services	0.010	0.013*	-0.002	0.007
	(0.014)	(0.007)	(0.011)	(0.009)
Services	-0.310	-0.062	-0.248	-0.268
	(0.269)	(0.144)	(0.231)	(0.246)
Observations	7463	7463	7463	7461
Number of firms	2431	2431	2431	2431
P-value Hansen test	0.703	0.00196	0.837	
P-value AR(2)	0.152	0.373	0.701	

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Regressions include worker and firm characteristics (% non open-ended, % part-time, firm size, % workers with >10 years of tenure, % white collars, capital stock), industry (8 dummies) and time dummies (7). In GMM first and second lags of explanatory variables are used as instruments.

Appendix B: KIA and ICT taxonomies

B.1 Knowledge intensive activities (KIA, Eurostat)

An activity 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 activity. The definition is built based on average number of employed persons aged 25-64 at aggregated EU-27 level in 2006, 2007 and 2008 according to NACE Rev. 1.1 at 2-digit, using EU Labour Force Survey data.

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).

More info at http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/Annexes/htec_esms_an7.pdf

B.2 ICT industries (O'Mahony and van Ark, 2003)

A sector is defined ICT intensive if it uses or produces ICT goods and services.

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).

Table B.1: Correlation coefficients between the HT/KIS, KIA and ICT taxonomies.

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