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JEL Classifications: J28, I2, J24, M50.

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ULB

Does corporate social responsibility make over-educated workers more productive?

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I. Introduction

This paper investigates how corporate social responsibility (hereafter, CSR) affects the role of the worker's level of education in determining firm productivity. Education has been a major concern in many European countries; one of their aims has been to increase the workers' level of education over the years. 34.6% of Europeans had attained tertiary education in 2011, compared to only 22.4% in 2000 (European Commission, 2012). In addition, the European Union's target (2009) is to reach 40% of tertiary educated workers aged between 30 and 34 by 2020.

However, a situation called over-education may appear when this increasing number of highly educated workers ceases to match the firms' requirements (Freeman, 1976). This phenomenon thus represents the inadequacy between a worker's attained level of education and the level of education required for his job. Therefore, a worker is considered to be over-educated if his level of education is higher than the level of education required to perform his job.[1] This phenomenon is also called in the over-education literature as vertical mismatch.[2] The European Union (2012) shows that over-education concerned on average 15% of EU27 workers over the period 2001-2011, with differences registered between countries. For example, over-education concerns 5% of Finnish workers compared to 26% of Greecs workers. Therefore, the effects of such a phenomenon need to be investigated, but existing evidence goes in different directions (McGuinness 2006; Mavromars and McGuinness 2012; Verhaest and van der Velden, 2013). A first tide of studies focuses on the effects of over-education on wages and almost always report that over-educated workers earn more than their adequately educated colleagues in similar jobs (Duncan and Hoffman, 1981; Rumberger, 1987; Sicherman, 1991; Battu, Seaman and Sloane (1999); Van der Meer, 2006; McGuinness and Sloane, 2011; Verhaest and Omey, 2012; Sanchez-Sanchez and McGuinness, 2015). Following human capital theory (Becker, 1964), it is therefore generally concluded that the former are more productive than the latter. A second tide of studies investigates the impact of this educational mismatch on job satisfaction and other correlates of workers' productivity (Tsang, 1987; Tsang, Rumberger and Levin, 1991; Hersch, 1991; Büchel, 2002; Verhaest and Omey, 2006, 2009; McGuinness and Byrne, 2015), but these studies do not necessarily bring out the same conclusions.

In addition, these two approaches suffer from several methodological limitations. When considering human capital explanations, the idea that the effect of education on wages can be transposed as such to productivity should most probably be questioned (Mortensen, 2003). As

[1] Under-education may also arise, representing an attained level of education that is lower than the level of education required to perform a job.

[2] A growing literature also focuses on the incidence and consequences of *horizontal* mismatch, i.e. the mismatch between the individual's field of education and his/her occupation. Morgado *et al.* (2015), for instance, suggest that between 20 and 50% of workers are horizontally mismatched in EU countries. In terms of outcomes, the pioneering paper by Robst (2007), based on US data for college graduates, shows that individuals with a major subject that does not match their work have an annual income penalty of around 11% compared to their well-matched opposite numbers. Nordin et al. (2010) report that this income penalty is even bigger in Sweden (12 and 20% for women and men, respectively). To sum up, horizontal mismatch is an important but still under-researched phenomenon (Verhaest *et al.*, 2015). In particular, it would be highly informative if we knew the effect of horizontal mismatch on productivity (rather than on wages or job satisfaction). Unfortunately, our data set provides no information on the worker's field of education. Therefore, we have chosen in this paper to focus on the productivity effects of *vertical* mismatch (over-education) in interaction with CSR.

for job satisfaction investigations, empirical results show that satisfaction is only correlated with job performance at a 30% level (Judge *et al.*, 2001). It is thus quite misleading to focus only on job satisfaction to evaluate the productivity effects of educational mismatch. However, the main methodological shortcoming of those studies is that they do not address the effect of educational mismatch on productivity *directly*, but always indirectly. As Hartog (2000) explains, it would be interesting to know the direct effect of over-education on productivity, rather than their indirect effects through wages, job satisfaction, and other correlates. To our knowledge, Kampelmann and Rycx (2012) and Grunau (2015) are the first to settle the basis of a direct investigation of the impact of educational mismatch on firm productivity. However, their conclusions let the door open for other developments. For example, it would be interesting to investigate whether specific firm decisions may influence the previously documented productivity implications.

The contribution of this paper is to provide first evidence on whether the impact of the worker's level of education on firm productivity varies according to the firm's voluntary approach to implement a CSR process. More precisely, the ISO 26000, by defining six CSR dimensions, one of which concerning the relations with workers and their working conditions, provides guidance to firms that implement a CSR approach. The originality of this paper lies in the fact that we investigate how this dimension of CSR, measured through three different indicators, may influence the relationship between over-education and firm productivity, considering that such policies are supposed to create a specific working environment that aims at enhancing workers' productivity (McGuire, Sundgren and Schneeweis, 1988; Daubas-Letourneux, 1998; Callens and Tyteca, 1999; European Commission, 2001; Ortega and Rioux, 2002; Levine and Parkin, 2002; Dubigeon, 2005; Coulon, 2006; De Serres, Gendron and Ramboarisata, 2006; Becchetti, Di Giacomo and Pinnacchio, 2008; Beaupré *et al*., 2008; Bonnechère, 2008). In order to address these issues, we use an econometric specification linking over-education and firm productivity at the firm level, and consider the average firm-level value added per worker as dependent variable. We thus estimate how mean years of over-education within firms affects the productivity of these firms (conditional on mean years of required education) in the whole private sector and according to the socially responsible policy of the firm. Our dataset allows us to control for a large range of worker and firm characteristics, which enables us to address important methodological issues such as firm-level time-invariant heterogeneity, endogeneity, and dynamics in the adjustment process of productivity. To do so, we rely on the dynamic system GMM estimator developed by Arrelano and Bover (1995) and Blundell and Bond (1998).

The rest of this paper is organised as follows. In Section 2, we review the literature. In Sections 3 and 4, we respectively detail our methodology and dataset. We then present our results in Section 5. Finally, we discuss our results and conclude in the last section.

II. Literature review

Educational mismatch and productivity

Considering the impact of educational mismatch on firm productivity, two different approaches can be found in the microeconometric literature. The first trend of research is based on human capital theory (Becker, 1964), according to which education allows to develop capabilities that make workers more productive. Gaps between workers' earnings

would thus reflect these different levels of productivity. To this end, the impact of over-education on productivity could be evaluated through its impact on wages. This way of doing is notably followed by Rumberger (1987), who finds that the impact of over-education on wages is significantly positive but lower than the impact of required education. He then concludes that, seemingly, surplus schooling (that is, over-education) is not counterproductive, but jobs prevent workers from fully using their skills. Other researchers also find that over-education has a positive effect on wages. If we refer to human capital theory, this implies that over-education increases workers' productivity (Duncan and Hoffman, 1981; Sicherman, 1991; Battu, Seaman and Sloaneer, 1999; Van der Meer, 2006; Dolton and Silles, 2008; McGuinness and Sloane, 2011).

The second trend of research is based on the relationship between over-education and job satisfaction or other correlates of workers' productivity, such as absenteeism, turnover or shirking. According to these studies (Vroom, 1964), over-educated workers are frustrated in their job because they are not fully using their skills. They are consequently unsatisfied, more often absent, and sicker than their adequately educated colleagues. Firms are then less inclined to hire these over-educated workers as they may have a negative impact on productivity. However, empirical results reveal that this hypothesis is not always validated. Hersh (1991), for example, finds that over-educated workers are less satisfied than their adequately educated peers and that over-educated male workers are more likely than other workers to quit their jobs. Tsang, Rumberger and Levin (1991) confirm these findings, except for estimations about over-educated female workers. Tsang (1987) also investigates the impact of over-education on job satisfaction by constructing a firm-level job satisfaction index. He evaluates the effect of this job satisfaction index on productivity and finds (i) that over-education decreases job satisfaction, and (ii) that job satisfaction is positively related to output. He thus concludes that over-education negatively impacts workers' productivity. Verhaest and Omey (2006), using Belgian data on Flanders, are unable to validate the negative impact of over-education on job satisfaction, even if they show that over-educated workers register a higher turnover. Later, using an extension on this dataset on Flanders, Verhaest and Omey (2009) find a significant, negative impact of over-education on job satisfaction. They also show that this negative impact decreases with the number of years of experience. Conversely, Büchel (2002) shows that there is no significant impact of over-education on job satisfaction and even finds that over-educated workers tend to be healthier, more work- and career-minded, and have a lower turnover.

As it is, these two main trends of research do not reach the same conclusion: the human capital theory supposes that over-educated workers are more productive, whereas studies based on job satisfaction suggest otherwise. In addition, these two approaches suffer from several methodological limitations. The human capital theory suggests that the level of education has the same influence on productivity as on wages. However, the relationship could be more complex than this. Spence (1973) develops the signalling theory, according to which workers' productivity is related to personal factors such as the workers' background, history, or talent. He states that education is simply used as a signal for an applicant to demonstrate his abilities to a potential future employer. Thus, wages cannot be directly linked to productivity in every case. Furthermore, in non-competitive models of wage determination, such as rent-sharing, collective bargaining, discrimination, or monopsony models, wages do

not only reflect productivity, and we may find two workers with similar productive characteristics that have different wages (Manning, 2003; Mortensen, 2003; Blanchflower and Bryson, 2010). As for job satisfaction, many studies seem to ignore that it is not the only characteristic that influences workers' productivity through education (Judge *et al.*, 2001). Therefore, even if an over-educated worker is less satisfied in his job, and even if an unsatisfied worker has higher chances of being less productive as such, this worker may have acquired skills during his schooling that allow him to compensate the negative effect of job satisfaction on productivity.

The main shortcoming of those studies is that they all question the impact of over-education on productivity indirectly. This has already been noted by Hartog (2000), who states that it would be interesting to evaluate the direct effect of over-education on productivity, rather than their indirect effect through wages, job satisfaction or other related workers' characteristics. To our knowledge, Kampelmann and Rycx (2012) are the first to investigate the direct impact of educational mismatch on firm productivity (*i.e.*, on the value added per worker). They show that the level of required education is positively and significantly related to firm productivity, and that additional years of over-education are beneficial to workers' productivity. Their conclusions open the door to further developments.

The role of corporate social responsibility

As mentioned previously, an interesting avenue for research is to evaluate whether or not the impact of over-education on direct measures of firm productivity varies in specific working conditions. This paper specifically aims at investigating how the relationship between over-education and firm productivity varies according to the firm's investment in a CSR process. The concept of CSR, which sets an equilibrium between organizations', stakeholders' and workers' benefits/well-being, may offer the opportunity to improve firm performance, working conditions, and firm longevity (ORSE, 2009). It has been defined widely by various researchers (Bowen, 1953; Freeman, 1984; Igalens and Joras, 2002; Chauveau and Rosé, 2003; Jamali, 2008; Lindgreen, Swaen and Wesley, 2008). Frederick (1960), for example, defines CSR as a civic behaviour towards economic and/or human resources.

As far as international legislation is concerned, the ISO 26000 provides guidance on how firms may implement socially responsible actions. More specifically, the ISO 26000 is an approach to risk management with a significantly expanded scope of responsibility and incentive to the overall performance and technical, managerial and ethical innovation (Provost-Vanhecke and Sibille, 2013).

The responsibility of an organization in terms of its decisions' and activities' impacts on the society as well as on the environment (i) takes into account the expectations of stakeholders, (ii) respects the law, and (iii) is consistent with international norms of behaviour. This responsibility is integrated throughout the organization and implemented in the organization's relationships (Aubrun *et al.*, 2010). Even if it provides guidance rather than requirements, a scope defining responsible corporate governance suggests that CSR should be applied to:

- Human rights (duty of care, discrimination, remediation to non-respect, civil and political rights, socio-economic rights);

- Relationship with workers and working conditions (employment and relationships between employer and employee, working conditions and social protection, social dialogue, health and safety at work, human capital development);
- Environment (pollution prevention, sustainable use of natural resources, respect of the biodiversity and of areas of natural land);
- Good practices in business (social political commitment, fight against corruption, fair competition, property right);
- Consumers and social commitments (sustainable consumption, education and awareness, external community, after-sales services);
- Community and local development **(**involvement, education and culture, employment and skills, technology and access, wealth creation, health, investment in society).

In the database at our disposal, one of these parameters of CSR may be questioned, *i.e.* the relationship with workers and working conditions. Indeed, socially responsible firms are supposed to create a positive and comfortable working climate, so that workers may feel better in such an environment. In order to measure the firm's willingness to implement a favourable social climate in terms of CSR, we design three complementary indicators, defined as (i) Matching, (ii) Diversity, and (iii) Long-term relationship.

Matching the worker's level of education. The first CSR indicator we address is the firm's willingness to hire workers in jobs that best match their level of education. The assumption is that these firms would not try to take advantage of the excess of supply in the labour market by hiring workers with a higher level of education than what is required for the job. These firms, described as "playing the game", would thus be those that decide to keep a certain balance between the job requirements and the corresponding worker's level of education. One of the main consequences would be a better social climate in the firm, since there would be no *substantial* number of workers who do not match the requirements (i) affecting productivity negatively by feeling underpaid in comparison with their real capabilities, (ii) perceived by other workers as a way for the firm to lower salaries in order to generate extra profit from their productivity. In the end, workers would be more motivated (Callens and Tyteca, 1999) and would stay longer in these firms (European Commission, 2001). Other studies tend to confirm this hypothesis and show that, when they are operating in firms that take their well-being, the quality of their jobs and their working environment into account, workers are more sensitive to the social climate of the firm, which results in higher levels of performance (McGuire, Sundgren and Schneeweis, 1988; Beaupré *et al.*, 2008; Becchetti, Di Giacomo and Pinnacchio, 2008). Dubigeon (2005) states that "a socially responsible firm increases its efficiency and […] improves the productivity of its resources" (Dubigeon, 2005, p.30) and that a firm with a strong social responsibility policy "increases its productivity by creating sense and respect, by encouraging employees to develop themselves" (Dubigeon, 2005, p.30), thus by establishing a positive social climate through the matching of employees and firm values.

Promoting gender or age diversity. The second CSR indicator we address is the firm's willingness to hire workers regardless of their gender, age, or any other discriminating aspect. It thus focusses on discrimination and diversity issues (De Serres, Gendron and

Ramboarisata, 2006). A firm engaged in a socially responsible process would promote equity initiatives in terms of hiring decisions regardless of gender, age, minorities, workers' disabilities, etc. As suggested by Beaupré *et al.* (2008), in a CSR perspective, a firm must instil its organizational culture through respect and tolerance. By implementing non discriminatory policies, for example through equal pay for men and women, firms may improve the workers' working conditions and, in turn, create a positive social climate that enhances productivity (Coulon, 2006; Kagnicioglu and Kagnicioglu, 2007; Beaupré *et al.*, 2008). As for age, even though the abilities and aptitudes of ageing workers seem to decrease with age and other non-desirable characteristics such as inflexible attitudes or resistance to changes may appear (Chiu *et al.*, 2001), it is shown that these workers, when interacting with younger ones, may establish a mentorship relation that allows workers to develop their skills through knowledge sharing. This, in turn, may increase workers' productivity (Bouhris, Dubé and Jacob, 2004).

Opting for a long-term relationship with workers. The third CSR indicator we address is the firm's willingness to establish a long-term relationship with its workers, through longer-term labour contracts or longer tenure perspectives. We basically find two types of labour contracts in working life (Ortega and Rioux, 2002): temporary or fixed-term contracts (hereafter FTCs) and permanent or indefinite-term contracts (hereafter ITCs). Favouring the latter may enhance firm productivity as ITCs contribute to the workers' quality of life and to the improvement of their performance, so that this type of contract is and should remain the main form of employment relationship (Bonnechère, 2008).

Other authors find that ITCs increase productivity since they offer job stability and allow workers' autonomy. According to Daubas-Letourneux (1998), ITCs allow workers to have higher degrees of autonomy in their work, for example in terms of schedule, or a working method they can choose to change, etc. Moreover, Dubigeon (2005) states that ITC workers prefer working in responsible firms favouring permanent rather than temporary contracts, and that it enhances their productivity. Finally, according to Levine and Parkin (2002), ITCs are used to establish the company in a better environment and to improve workers' productivity.

III. Methodology

The econometric specification

In the literature on educational mismatch, we can find three different ways to measure the level of required education for a job, each measure having its own advantages and weaknesses. These measures are based respectively on job analysis, worker self-assessment and realized matches (see e.g. Hartog, 2000 for further information on each measure). Given the characteristics of our data, we rely on the latter measure in this paper. We thus compute the level of education required for a given job by taking the mode of workers' years of education within each ISCO 3-digit level of occupation.[3] A worker is then defined as over-educated if his attained level of education is higher than the one required in his occupation.

[3] The educational attainment of a worker is available in seven categories in our dataset. This information, reported by firms' human capital departments (on the basis of their registers), has been transformed into years of education. We then applied the following rule: (i) primary education: 6 years of education; (ii) lower secondary education: 9 years of education; (iii-iv) general, technical and artistic upper secondary education: 12 years of

To evaluate the impact of over-education on firm productivity, we adopt the empirical strategy developed by Kampelmann and Rycx (2012). Hence, we estimate the following firm-level equation:

$$\ln VA_{j,t} = \beta_0 + \beta_1\left(\ln VA_{j,t-1}\right) + \beta_2\left(\frac{1}{m_{j,t}}\sum_{i=1}^{m_{j,t}} O_{i,j,t}\right) + \beta_3\left(\frac{1}{m_{j,t}}\sum_{i=1}^{m_{j,t}} R_{i,j,t}\right) + \beta_4 X_{j,t} + \beta_5 Z_{j,t} + \gamma_t + \vartheta_{j,t} \quad (1)$$

with:

(a) $VA_{j,t}$ the productivity of firm *j* at year *t*, measured by the average value added per worker.

(b) $m_{j,t}$ the number of workers employed in firm *j* at year *t.*

(c) $R_{i,j,t}$ the required years of education for the worker's job *i* in firm *j* at year *t*, i.e. the mode of years of education in worker's *i* occupation at ISCO (International Standard Classification of Occupations) 3-digit level (across the entire economy) at time *t*.

(d) $O_{i,j,t} = \left(Attained\_education_{i,j,t} - REQ_{i,j,t}\right)$ if > 0, 0 otherwise.

(e) $Attained\_education_{i,j,t}$ the number of years corresponding to the highest level of education attained by worker *i* employed in firm *j* at time *t*.

(f) $X_{j,t}$ a vector containing aggregated characteristics of workers in firm *j* at year *t*: the share of the workforce that has at least 10 years of tenure, the fractions of workers respectively younger than 30 and older than 49, and the shares of women, blue-collar, and part-time workers.

(g) $Z_{j,t}$ includes firm characteristics, i.e. the sectorial affiliation (8 dummies), size (number of workers) of the firm, the conditional dispersion in hourly wages, and the level of wage bargaining (1 dummy).

(h) γ_t is a set of 11 year dummies.

(i) $\vartheta_{j,t}$ is the error term.

This equation describes the relationship between average years of over- and required education within firms and productivity, while controlling for years dummies and mean worker and firm characteristics.[4] Including the lagged dependent variable among the regressors allows us to account for the potential state dependence of firm productivity[5] and aims to improve the estimates of the parameters of interest in our preferred specifications (see below).

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education; (v) higher non-university education, short: 14 years of education; (vi) university and non-university education, long: 16 years of education; (vii) post-graduate education: 17 years of education.

[4] Note that we also control for mean years of under-education.

[5] The assumption of persistent productivity both at the industry and firm level is strongly supported by the literature (see e.g. Baily, Hulten and Campbell, 1992; Bartelsman and Doms, 2000). Researchers 'documented, virtually without exception, enormous and persistent measured productivity differences across producers, even within narrowly defined industries' (Syverson, 2011: 326). Large parts of these productivity differences are still hard to explain. This implies that productivity at time *t* in a given industry or firm is likely to depend significantly on its lagged value. This implies that there are strong arguments for modelling productivitty in a dynamic way, i.e. for including the lagged dependent variable among covariates in Equation (1).

The role of corporate social responsibility

We then make the impact of over-education on firm productivity interact with the propensity of a firm to implement a CSR policy, that we design through three indicators: (i) matching the worker's level of education and the job requirements, (ii) promoting gender and age diversity, and (iii) opting for a long-term relationship with workers. To this end, for each CSR indicator, we estimate equation (1) for the group of firms defined as socially responsible in our panel in order to test whether implementing a CSR policy fosters workers' productivity.

Matching the worker's level of education. In order to distinguish firms that are socially responsible in terms of hiring decisions from firms that are not, we define a firm as socially responsible if the majority of its workers are hired for jobs that match their attained level of education. The firm thus has a proportion of over- and under-educated workers lower than the mean of all the firms belonging to the same NACE 3-digit industry.

Promoting gender or age diversity. To distinguish socially responsible firms in terms of diversity policies from those that are not, we define a firm as socially responsible if it has a bigger proportion of women and older workers than the mean of all the firms belonging to the same NACE 3-digit industry.

Opting for a long-term relationship with workers. Finally, in order to test whether the relationship between educational mismatch and productivity depends on the firm's willingness to engage in a long-term relationship with its workers, we define a firm as socially responsible if it has a higher propotion of permanent labour contracts and higher average years of tenure per worker than the mean of all the firms belonging to the same NACE 3-digit industry.

The estimation technique

We estimate the econometric specification with three different methods: (i) pooled ordinary least squares (hereafter, OLS), (ii) a fixed-effects model (hereafter, FE), and (iii) the generalized method of moments (hereafter, GMM) estimator. The OLS estimator with standard errors robust to heteroscedasticity and serial correlation is based on the cross-section variability between firms and the longitudinal variability within firms over time. However, it suffers from a potential heterogeneity bias because firm productivity can be related to firm-specific, time-invariant characteristics that are not measured in micro-level surveys, such as an advantageous location or firm-specific assets (*e.g.*, patent ownership).

In order to take into account unobserved time-invariant firm characteristics, we use a FE model. However, neither pooled OLS nor the FE estimator is able to address the potential endogeneity of our explanatory variables.[6] Yet, there might be some cyclical 'crowding out', that is, a process by which highly educated workers take jobs that could be occupied by less educated ones during recessions, because of excess labour supply. This assumption suggests that mean years of over-education within firms may increase in response to a lower labour

[6] Expected biases associated with OLS and the relatively poor performance and shortcomings of the FE estimator in the context of firm-level productivity regressions are reviewed in Van Beveren (2012).

productivity (and vice versa). To control for this endogeneity issue, we re-estimate equation (1) with the dynamic system GMM estimator.

The dynamic system GMM approach boils down to simultaneously estimating a system of two equations (one in level and one in first differences) and relying on internal instruments to control for endogeneity. More precisely, over-education and other endogenous input factors are instrumented by their lagged levels in the differenced equation and by their lagged differences in the level equation. The implicit assumption is that differences (levels) in (of) productivity in one period, although possibly correlated with contemporaneous differences (levels) in over-education, are uncorrelated with lagged levels (differences) of (in) the latter. Moreover, differences (levels) in (of) over-education are assumed to be reasonably correlated with their past levels (differences).

One advantage of *system* GMM is that time-invariant explanatory variables can be included among the regressors, whereas they typically disappear in difference GMM. Asymptotically, the inclusion of these variables does not affect the estimates of the other regressors, because instruments in the level equation (*i.e.*, lagged differences of over-education) are expected to be orthogonal to all time-invariant variables (Roodman, 2009). To examine the validity of our estimations, we apply Hansen's (1982) and Arellano-Bond's (1991) tests. The first is a test for overidentification that allows to test the validity of the instruments. The second is a test for autocorrelation, where the null hypothesis assumes no second order autocorrelation in the first differenced errors. The non-rejection of the two tests is required if we want to assume that our estimations are reliable. In order to be as parsimonious as possible, we choose the model with the minimum number of lags that passes both tests.

The adoption of a *dynamic* GMM specification is likely to improve the identification of the parameters of interest (even though the coefficient of the lagged dependent variable is not a central issue in the analysis). Indeed, as illustrated by Bond (2002), the use of a dynamic model is necessary to obtain consistent results when estimating a production function with serially correlated productivity shocks and explanatory variables that are correlated with these shocks. While serial correlation of productivity shocks may arise if, *e.g.*, "the effects from demand shocks are only partially captured by the industry-specific control variables" (Hempell, 2005), the responsiveness of input factors to productivity shocks may be explained by the above-mentioned endogeneity issue. Interestingly, the inclusion of the lagged dependent variable in the OLS, FE and system GMM specifications also provides an *ad hoc* test for the appropriateness of the latter. As outlined by Roodman (2009), this test consists in checking whether or not the regression coefficient on the lagged dependent variable obtained with system GMM falls between the OLS and FE estimates.

IV. Dataset

In order to test our different hypotheses, we use a combination of two large datasets covering the years 1999-2010, carried out and merged by Statistics Belgium using the firms' social security numbers. The first is the "Structure of Earnings Survey" (SES), which covers all firms that: are operating in Belgium, employ more than 10 workers and have economic

activities within sections B to N of the NACE Rev. 2 nomenclature.[7] This survey gathers information on firms' characteristics (*e.g.*, sector, number of workers, level of collective wage bargaining) as well as information on workers' characteristics (*e.g.*, age, education, tenure, gross earnings, paid hours, gender, occupation). However, the SES does not provide any financial information. It has thus been merged with a firm-level survey, namely the "Structure of Business Survey" (SBS), also carried out by Statistics Belgium. This survey provides financial information (*e.g.*, firm-level value added, gross operating surplus per worker, etc.). The coverage of the SBS is not the same as that of the SES, as it does not cover the entire financial sector (NACE K).

A specificity of this SES-SBS association is that the data from the SES relates each year to the month of October, whereas that from the SBS refers to each month, from January to December. To avoid running a regression where information on the dependent variable (collected for the entire year) precedes the recording of the explanatory variables (collected in October), all explanatory variables in equation (1) have been lagged by one year. That is, the information about educational mismatch relative to October in year t is used to explain the productivity of the firm in year $t+1$. The imperfect synchronization between the SBS and SES data may introduce fuzziness into our estimates, and we cannot exclude potential external events influencing productivity in the intermediate period. Relying on firm-level information on over-education for the entire calendar year would allow us to completely eliminate this concern. This being said, even if this information were available, there is a compelling argument for using asynchronised information on over-education: it is difficult to conceive how changes in over-education could generate *immediate* effects, and potential productivity effects are thus more likely to occur after a certain adjustment period. The slightly asynchronised use of SBS and SES is therefore arguably the best option in light of data availability and productivity dynamics.

Accordingly, this leads to a restriction of the sample to firms observed for at least two consecutive years, which leads to an over-representation of medium-sized and large firms since the sampling percentages for each firm in our dataset increase with the size of the firm.[8]

[7] The following sectors are included: Mining and quarrying (B), Manufacturing (C), Electricity, gas, steam and air conditioning supply (D), Water supply, sewerage, waste management and remediation activities (E), Construction (F), Wholesale and retail trade, repair of motor vehicles and motorcycles (G), Transportation and storage (H), Accommodation and food service activities (I), Information and communication (J), Financial and insurance activities (K), Real estate activities (L), Professional scientific and technical activities (M), Administrative and support service activities (N).

[8] The SES is a stratified sample. The stratification criteria refer respectively to the region (NUTS-groups), principal economic activity (NACE-groups) and size of the firm. The sample size in each stratum depends on the size of the firm. The sampling percentages of firms are respectively equal to 10, 50, and 100 percent when the number of workers is below 50, between 50 and 99, and above 100. Within a firm, the sampling percentages of employees also depend on size. The sampling percentages of employees reach respectively 100, 50, 25, 14.3, and 10 percent when the number of workers is below 20, between 20 and 49, 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 300 to 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

Moreover, we exclude workers and firms for which data is missing or inaccurate.[9] In addition, in order to guarantee that the level of required education is computed on the basis of a sufficient volume of data, we choose to eliminate occupations at ISCO 3-digit level with less than 10 observations.[10] Finally, we eliminate firms with less than 10 observations, because the use of average values at the firm level requires a suitable number of observations.[11] Our final sample covering the period 1999-2010 consists of an unbalanced panel of 12,290 firm-year observations from 3,913 firms. It is representative of all medium-sized and large firms in the Belgian private sector[12], with the exception of parts of the financial sector (NACE K) and the electricity, gas and water supply industry (NACE D+E).

[Insert Table 1 about here]

Descriptive statistics of selected variables are presented in Table 1. They show that the annual firm-level value added per worker represents on average 91,876 EUR. The mean number of required years of education at the firm level equals 12.01 and the proportion of over-educated workers stands at around 20 percent. Put differently, average years of over-education within firms are equal to 0.53. Moreover, we find that 4% of workers are employed under temporary labor contracts, while 96% are employed under permanent labor contracts. Around 28% of employees within firms are women, 52% are blue-collars, 61% are prime-age workers (*i.e.*, between 30 and 49 years old), 37% have at least ten years of tenure, and 16% are part-time workers (*i.e.*, work less than 30 hours per week). Firms have an average of 250 employees and are concentrated essentially in the following sectors: manufacturing (53%); wholesale and retail trade, repair of motor vehicles and motorcycles (15%); real estate activities, professional scientific and technical activities, administrative and support service activities (13%); and construction (9%).

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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).

[9] For instance, we eliminate a (very small) number of firms for which the recorded value added was negative.

[10] Some robustness tests have been done with the threshold fixed at 50 observations. Given that the number of data points per occupation at the ISCO 3-digit level is quite large, this alternative threshold has little effect on sample size and leaves results unaffected.

[11] As it leads to a very small drop in sample size, this restriction is unlikely to affect our results.

[12] Larger firms are likely to employ a lower share of over-educated workers because they generally have more sophisticated HRM procedures (notably in terms of recruitment) and a wider range of jobs (Dolton and Silles, 2001). Moreover, the required level of education is probably better defined in bigger firms. As a result, the fact that medium and large firms are over-represented in our sample may under-estimate the incidence of over-education. Yet, caution is required. Indeed, empirical results provided by Karakaya et al. (2007) suggest that the impact of firm size on over-education is very weak in the Belgian private sector. Using matched employer-employee data for 1995, the authors suggest that the likelihood for a worker to be over-educated decreases by only 0.1% *ceteris paribus* if firm size increases by 100 extra workers.

V. Results

The overall specification

We first estimate equation (1) by OLS with standard errors robust to heteroscedasticity and serial correlation. The results presented in the second column of Table 2 show that lagged productivity significantly affects its current value. Then, increasing the level of required education significantly and positively impacts firm productivity, which is expected to increase by 1.3% the year after a one-unit increase in mean years of required education. Concerning over-education variable, the results show that over-education exerts a significant, positive impact on firm productivity. Firm productivity increases on average by 1.8% the year after a one-unit increase in mean years of over-education.

[Insert Table 2 about here]

However, as mentioned previously, the two main shortcomings of these estimates are that time-invariant unobserved workplace characteristics are not controlled for and that the relationship may suffer from the endogeneity of over-education variable.[13] To control for these potential biases, we re-estimate equation (1) using the dynamic system GMM estimator.[14] In order to examine the consistency of our estimates, we apply Hansen's (1982) and Arellano-Bond's (1991) tests. As reported in the third column of Table 2, these two tests respectively do not reject the null hypothesis of valid instruments and of no second order autocorrelation. So, the results reliably show that current productivity is significantly and positively related to its lagged value. Concerning the level of required education, our results show that firm productivity is expected to increase by 2.3% following a one-unit increase in mean years of required education. Moreover, the coefficient of over-education remains significant and suggest that firm productivity increases on average by 2.3% following a one-unit increase in mean years of over-education.[15]

[13] The FE estimator only controls for the potential bias related to the time-invariant unobserved workplace characteristics. So, only GMM results are further reported. FE results are available on request.

[14] Interestingly, the GMM coefficient on the lagged dependent variable falls between the OLS and FE estimates (available on request). As highlighted by Roodman (2009), this result supports the appropriateness of our dynamic system GMM specification.

[15] Detailed dynamic system GMM estimates, including control variables, are available on request. Regression coefficients associated to the covariates are in line with earlier findings. Most sectoral dummies, for instance, are significant and they follow a similar pattern than that reported in the literature on inter-industry wage differentials (see e.g. du Caju et al., 2012). Among the highly productivity sectors, we notably find the electricity, gas and water supply industry (NACE D and E) and financial and insurance activities (NACE K). Not surprisingly, as shown in du Caju et al. (2011), these sectors are also found at the top of the conditional wage distribution. The coefficient on part-time is found to be significantly negative. This corroborates estimates of Specchia and Vandenberghe (2013) and Devicienti et al. (2015) showing that firms employing more part-timers are *ceteris paribus* less productive. An insignificant coefficient for blue-collar workers is also reported in Kampelmann and Rycx (2012). The authors find that occupations play different roles for remuneration and productivity in the Belgian private sector. While their estimations indicate a significant upward-sloping occupational wage-profile, they cannot reject the hypothesis of a flat productivity-profile. Finally, the insignificant coefficient associated to the share of women is in line with Garnero et al. (2014). The latter show that women are associated to economic rents. More precisely, their findings for the Belgian economy show that increasing the share of women within firms has no significant impact on productivity but decreases the average wage bill. Put differently, firms employing a larger proportion of women would be more profitable.

Although estimates reported so far address a range of econometric issues, they could nevertheless be misleading given that our over-education variable does not control for the birth cohort of workers. Indeed, given that years of education have substantially increased over time and that professional experience could be a substitute to formal education, it may be more appropriate to determine whether a worker is over-educated by comparing his level of education with the mode of the education among workers of a similar generation employed in the same occupation. Hence, we re-estimated equation (1) controlling for birth cohort effects. Practically, according to the methodology outlined in Kamplemann and Rycx (2012), we considered two age groups, fixed the threshold to separate young from older workers at 35 years and defined a worker as over-educated if his level of education is higher than the one required for workers belonging to the same age group and occupational category at the ISCO 3-digit level. Results, presented in the second column of Appendix Table A.1, support the consistency of our estimates. Indeed, they show again that: (i) productivity depends positively and significantly on average required years of education within firms, and (ii) mean years of over-education have a significant and positive effect on firms' value added. Also noteworthy is that the magnitude of the regression coefficients associated to required and over-education is not very different than in our benchmark regression (see third column Table 2). Overall, it thus appears that our conclusions remain unchanged after controlling for the birth cohort of workers.

A complementary issue is that our indicator of over-education is more likely to represent a real mismatch in skills for new labour market entrants. Indeed, skills learned at school tend to depreciate over time so that older workers are less likely to have skills in excess of those required for their job. Moreover, over-education is very sensitive to workers' professional experience and thus probably a less relevant measure among older workers. To test the impact of over-education on productivity for young and older generations of workers, we included as explanatory variables in our benchmark equation (that does control for cohort effects) mean years of over-education respectively among young and older workers in each firm (keeping the age threshold at 35 years). Results obtained with the dynamic system GMM estimator are reported in the third column of Appendix Table A.1. They show that over-education exerts a significantly positive impact on productivity both among young and older workers. Interestingly, results also show that the return to over-education decreases with workers age. They thus suggest that over-educated workers are more productive all over their career due to additional skills and capabilities acquired through schooling. Yet, they also suggest that these additional skills and capabilities depreciate as time goes by.

The role of corporate social responsibility

Matching the worker's level of education. We first investigate whether the first CSR indicator, *i.e.* the firm's willingness to match the workers' level of education with the jobs requirements, may influence the relationship between educational mismatch and firm productivity. We thus bring out firms that implement such a policy, which represents 3,563 firm-year observations out of our 12,290 firm-year global sample (29%) and apply our different sets of regressions.

[Insert Table 3 about here]

We first test the reliability of the results by applying Arellano-Bond's (1991) and Hansen's (1982) tests, mentioned previously. As reported in the second column of the Table 3, they do not reject the null hypothesis of no autocorrelation and the null hypothesis of valid instruments. The results show that current productivity is positively related to its one-period lagged value, but also that required and over-education have a significant and positive impact on firm productivity. Moreover, these results show that the impact of over-education is enhanced in firms that are implementing CSR policies as defined by the first indicator[16]. More precisely, a one-unit increase in mean years of required education leads, the next year, to a 3.0% rise in productivity for CSR firms, compared to a 2.3% increase for the whole sample of firms. Then, increasing mean years of over-education by one unit is estimated to increase productivity by 3.9% the next year in firms that implement such a policy, which is 1.6% more than the corresponding coefficient for the whole sample of firms. These results thus support the hypothesis that the expected positive social climate created by CSR behaviours enhances the productivity effects of required and over-education.

Promoting gender or age diversity. Secondly, we question whether CSR behaviours in terms of diversity decisions may increase workers' productivity. We thus select firms that wish to implement such a policy, which represents 2,336 firm-year observations out of our 12,290 firm-year global sample (19%), and run the same set of regressions as that for the whole sample of firms.

The results presented in the third column of Table 3 are based on the system GMM estimator. Both Hansen's and Arellano-Bond's tests show that we can rely on our results since the two tests respectively do not reject the null hypothesis of valid instruments and the null hypothesis of no autocorrelation. Thus, the results show that current productivity is positively and significantly related to its previous value. Moreover, each additional year of required education exerts a significant, 4.7% positive impact on firm productivity. Over-education also has a significant impact on productivity, and a one-unit increase in the mean years of over-education has a 5.5% positive impact on firm productivity the next year. These results also suggest that the impact of over-education is enhanced (see footnote 16) in firms that are implementing CSR policies as defined by the second indicator, with an additional 3.2% positive impact of over-education on productivity compared to the whole sample of firms.

Opting for a long-term relationship with workers. Finally, the third CSR indicator investigates the firm's willingness to engage in a long-term relationship with its workers. We select firms that offer a higher percentage of permanent labour contracts and that register higher mean years of workers tenure, which represents 5,489 firm-year observations out of our 12,290 global firm-year sample (45%), and run the previous set of regressions.

Again, we test the reliability of the results by applying Arellano-Bond's (1991) and Hansen's (1982) tests, previously mentioned. As reported in the fourth column of Table 3, the

[16] Note that we ran a test of differences between means in order to know whether a significant difference appears between the estimated parameters for the different subsamples, where the two parameters are not significantly different under the null hypothesis, while the two parameters are significantly different under the alternative. The results, showing that all coefficients are statistically different, are available on request.

two tests respectively do not reject the null hypothesis of no autocorrelation and the null hypothesis of valid instruments. We thus find that current productivity is positively and significantly related to its lagged value. The results also show that both the levels of required and over-education have a positive and significant impact in firms that implement a socially responsible approach as defined by our third indicator. More precisely, increasing the mean years of required education by one unit is estimated to increase productivity by 2.0% the next year in firms that are socially responsible. We reach a similar conclusion for over-education: increasing the level of over-education by one year is estimated to increase firm productivity by 3.5% the next year in these socially responsible firms, which is 1.2% more than the whole sample estimation. It thus seems that the impact of over-education on productivity is also enhanced (see footnote 16) in firms that implement a CSR policy as defined by the third indicator.

As a robustness test, we re-examined the role of corporate social responsibility in the relationship between over-education and productivity first by controlling for birth cohort effects and second by distinguishing the effect of over-education among young and older workers respectively. Dynamic system GMM estimates are reported in Appendix A.2, A.3 and A.4. On the one hand, they show that mean years of required and over-education still have a significantly stronger (positive) effect on productivity in firms implementing CSR practices when controlling for cohort effects. On the other, they confirm that the impact of over-education on firms' value added is more pronounced among young workers, which supports the idea that surplus knowledge acquired through schooling depreciates as time goes by.

VI. Discussion and conclusion

This paper provides first evidence on the moderating role of CSR in the relationship between over-education and productivity. More precisely, relying on detailed Belgian linked employer-employee panel data, we investigated whether the implementation of a socially responsible policy by a firm may influence the relationship between over-education and productivity. The CSR policy has been designed through three different indicators, referring to the chapter "Relations with workers and working conditions" defined in the ISO 26000: (i) the willingness to match workers with jobs that correspond to their level of education – Matching, (ii) the willingness to hire workers regardless of their gender and age – Diversity, and (iii) the willingness to engage in a long-term relationship with workers through permanent labour contracts and longer tenure – Long-Term Relationship. In order to address this issue, we i) used an econometric specification linking over-education and firm productivity at the firm level, ii) considered the average firm-level value added per worker as dependent variable, and iii) applied the dynamic system GMM estimator. We thus estimated how mean years of over-education impact firm productivity (conditional on mean years of required education) in the whole private sector and depending on the CSR policy implemented by the firm.

Controlling for a large range of covariates, time-invariant unobserved workplace characteristics, simultaneity issues, and dynamics in the adjustment process of productivity, we found that a higher level of required education exerts a significant, positive impact on firm

productivity, but also that increasing the level of over-education fosters firm productivity. These results can be reconciled with the literature on the wage effects of over-education, which suggests that over-educated workers earn more than workers possessing the required level of education because they are more productive than them. Conversely, these results do not support the hypothesis that over-educated workers are less productive than other workers because of their lower satisfaction.

Concerning the role of the socially responsible approach, we began with the first CSR indicator, which is the firm's willingness to best match workers with suitable jobs. Our results suggest that over-education exerts a significant and stronger positive impact on productivity in firms with less mismatched workers than in other firms operating in the same NACE 3-digit industry. These findings seem compatible with the idea that the positive social climate created by such policies may develop, encourage and increase over-educated workers' productivity (McGuire, Sundgren and Schneeweis, 1988; Dubigeon, 2005; Beaupré *et al.*, 2008).

The second CSR indicator we investigated leads to quite similar conclusions. That is, when a firm promotes diversity in terms of gender and age, our results suggest that over-educated workers' productivity is fostered when CSR is established. This provides support to the idea of Coulon (2006) or Beaupré *et al.* (2008) of a positive relationship between an improvement in the working conditions (through diversity/non discriminatory policies) and workers' productivity. It also appears to be in line with the hypothesis that older workers enhance productivity thanks to the mentorship relation they may establish (Bouhris, Dubé, and Jacob, 2004).

Finally, estimates associated to the third CSR indicator we designed support the idea that productivity effects of required and over-education are significantly stronger among firms establishing a long-term relationship with their workers. They thus support to the idea, suggested by Daubas-Letourneux (1998) and Dubigeon (2005), of a higher degree of autonomy and stability allowed by permanent labour contracts, which in turn leads to higher levels of productivity. They are also in line with the hypothesis that permanent contracts contribute to workers' quality of life and to the improvement of their performance (e.g. Bonnechère, 2008).

To sum up, our empirical investigation of the economic consequences of corporate social responsibility suggest that CSR is able to create a working environment that fosters the positive impact of both required and over-education on productivity. From a human capital perspective, it therefore suggests that socially responsible firms are more able than other firms to take advantage of (the surplus) knowledge of their (over-educated) workers.

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Table 1 - DESCRIPTIVE STATISTICS OF SELECTED VARIABLES, 1999-2010

Variables	Mean	Std. Dev.
Annual value added per worker[a] (€)	91,876	612,545
Required education (years)	12.01	1.36
Over-education		
Percentage of workers	20.35	22.08
Years	0.53	0.62
Workers with 10 years or more of tenure (%)	37.44	23.75
Women (%)	28.33	24.64
Blue-collar workers[b] (%)	52.39	35.22
Temporary workers (%)	4.00	9.23
Permanent workers (%)	96.00	
Share of workers < 30 years	21.78	14.73
Share of workers between 30 and 49 years	60.89	13.79
Share of workers > 49 years	17.33	12.51
Part-time (%)	16.40	17.55
Firm size (number of workers)	250.19	448.32
Firm-level collective agreement (%)	28.69	45.08
Sector (%)		
Mining and quarrying (B)	0.68	
Manufacturing (C)	52.66	
Electricity, gas, steam and air conditioning supply; Water supply, sewerage, waste management and remediation activities (D+E)	0.63	
Construction (F)	8.85	
Wholesale and retail trade, repair of motor vehicles and motorcycles (G)	15.28	
Accommodation and food services activities (I)	1.81	
Transport and storage ; Information and communication (H+J)	5.88	
Financial and insurance activities (K)	1.59	
Real estate activities ; Professional, scientific and technical activities ; Administrative and support service activities (L+M+N)	12.60	
Number of firm-year observations	12,290	

[a] At 2004 constant prices. [b] The distinction between blue- and white-collar workers is based on the International Standard Classification of Occupations (ISCO-08). Workers belonging to groups 1–5 are considered to be white-collar workers (1: Managers; 2: Professionals; 3: Technicians and associate professionals; 4: Clerical support workers; 5: Services and sales workers), and those from groups 7–9 are considered to be blue-collar workers (7: Craft and related trades workers; 8: Plant and machine operators and assemblers; 9: Elementary occupations).

Table 2 - EDUCATIONAL MISMATCH AND PRODUCTIVITY (OLS AND GMM ESTIMATES, 1999-2010)

Dependent variable	Value-added per worker (ln)	
	OLS	GMM-SYS[e]
Value added per worker (one year lagged, in ln)	0.886***	0.623***
	(0.018)	(0.043)
Required education (one year lagged, in years)	0.013***	0.023***
	(0.003)	(0.005)
Over-education (one year lagged, in years)	0.018***	0.023***
	(0.004)	(0.007)
Worker characteristics[b]	YES	YES
Firm characteristics[c]	YES	YES
Year dummies (11)	YES	YES
Adjusted R-squared	0.871	
Sig. model (p-value)	0.000	0.000
Hansen statistic		483.7
p-value		0.41
Arellano-Bond statistic (AR2)[d]		1.47
p-value		0.14
Number of firm-year observations	12,290	12,290

Notes:

[a] Robust standard errors are reported between brackets.

(***, **, *): Significant at respectively 1%, 5% and 10% levels.

[b] Shares of the workforce that: (i) has at least 10 years of tenure, and (ii) is younger than 30 and older than 49 years, respectively. The shares of women, blue-collar and part-time workers as well as the conditional dispersion in hourly wages are also included.

[c] Sectorial affiliation (8 dummies), number of workers, and level of wage bargaining (1 dummy).

[d] AR2 displays the test for second-order autocorrelation in the first-differenced errors.

[e] First and second lags of explanatory variables are used as instruments in the GMM specification, excluding time dummies.

Table 3 - EDUCATIONAL MISMATCH AND PRODUCTIVITY ACCORDING TO THE CSR (GMM ESTIMATES, 1999-2010)

Dependent variable	Value added per worker (ln)		
	Indicator 1 : Matching	Indicator 2 : Diversity	Indicator 3 : LT Relation
	GMM[e]	GMM[e]	GMM[e]
Value added per worker (one year lagged, in ln)	0.672***	0.654***	0.685***
	(0.064)	(0.130)	(0.045)
Required education (one year lagged, in years)	0.030***	0.047***	0.020***
	(0.009)	(0.017)	(0.006)
Over-education (one year lagged, in years)	0.039**	0.055***	0.035***
	(0.016)	(0.018)	(0.010)
Worker Characteristics[b]	YES	YES	YES
Firm Characteristics[c]	YES	YES	YES
Year dummies (11)	YES	YES	YES
Sig. model (p-value)	0.000	0.000	0.000
Hansen statistic	463.93	434.10	483.01
p-value	0.52	0.79	0.52
Arellano-Bond statistic (AR2)[d]	0.16	1.22	1.00
p-value	0.87	0.22	0.32
Number of firm-year observations	3,563	2,336	5,489

Notes:

[a] Robust standard errors are reported between brackets.

(***, **, *): Significant at respectively 1%, 5% and 10% levels.

[b] Share of the workforce that: (i) has at least 10 years of tenure, and (ii) is younger than 30 and older than 49 years, respectively. The share of women, blue-collar and part-time workers as well as the conditional dispersion in hourly wages are also included.

[c] Sectorial affiliation (8 dummies), number of workers, and level of wage bargaining (1 dummy).

[d] AR2 displays the test for second-order autocorrelation in the first-differenced errors.

[e] First and second lags of explanatory variables are used as instruments in the GMM specification, excluding time dummies

Table A.1 - EDUCATIONAL MISMATCH AND PRODUCTIVITY (GMM ESTIMATES, CONTROLLING FOR COHORT EFFECTS, 1999-2010)

Dependent variable	Value-added per worker (ln)	
	GMM-SYS[e]	GMM-SYS[e]
Value added per worker (one year lagged, in ln)	0.651***	0.660***
	(0.040)	(0.038)
Required education (one year lagged, in years)	0.029***	0.029***
	(0.005)	(0.005)
Over-education (one year lagged, in years)	0.022***	
	(0.007)	
Over-education among young workers		0.027*
(one year lagged, in years)		(0.016)
Over-education among older workers		0.020**
(one year lagged, in years)		(0.008)
Worker characteristics[b]	YES	YES
Firm characteristics[c]	YES	YES
Year dummies (11)	YES	YES
Adjusted R-squared		
Sig. model (p-value)	0.000	0.000
Hansen statistic	527.8	594.4
p-value	0.26	0.18
Arellano-Bond statistic (AR2)[d]	1.71	1.70
p-value	0.09	0.09
Number of firm-year observations	12,290	12,290

Notes:

[a] Robust standard errors are reported between brackets. ***, **, * significant at the 1, 5 and 10% level, respectively.

[b] Shares of the workforce that: (i) has at least 10 years of tenure, and (ii) is younger than 30 and older than 49 years, respectively. The shares of women, blue-collar and part-time workers as well as the conditional dispersion in hourly wages are also included.

[c] Sectorial affiliation (8 dummies), number of workers, and level of wage bargaining (1 dummy).

[d] AR2 displays the test for second-order autocorrelation in the first-differenced errors.

[e] First and second lags of explanatory variables are used as instruments in the GMM specification, excluding time dummies.

Table A.2 - EDUCATIONAL MISMATCH AND PRODUCTIVITY ACCORDING TO CSR INDICATOR 1 "MATCHING" (GMM ESTIMATES, CONTROLLING FOR COHORT EFFECTS, 1999-2010)

Dependent variable	Value-added per worker (ln)	
	GMM-SYS[e]	GMM-SYS[e]
Value added per worker (one year lagged, in ln)	0.671***	0.681***
	(0.066)	(0.061)
Required education (one year lagged, in years)	0.035***	0.034***
	(0.010)	(0.009)
Over-education (one year lagged, in years)	0.030**	
	(0.014)	
Over-education among young workers (one year lagged, in years)		0.059*
		(0.034)
Over-education among older workers (one year lagged, in years)		0.032**
		(0.014)
Worker characteristics[b]	YES	YES
Firm characteristics[c]	YES	YES
Year dummies (11)	YES	YES
Adjusted R-squared		
Sig. model (p-value)	0.000	0.000
Hansen statistic	464.0	461.1
p-value	0.52	0.56
Arellano-Bond statistic (AR2)[d]	-0.02	0.08
p-value	0.98	0.94
Number of firm-year observations	3,563	3,563

Notes:

[a] Robust standard errors are reported between brackets. ***, **, * significant at the 1, 5 and 10% level, respectively.

[b] Shares of the workforce that: (i) has at least 10 years of tenure, and (ii) is younger than 30 and older than 49 years, respectively. The shares of women, blue-collar and part-time workers as well as the conditional dispersion in hourly wages are also included.

[c] Sectorial affiliation (8 dummies), number of workers, and level of wage bargaining (1 dummy).

[d] AR2 displays the test for second-order autocorrelation in the first-differenced errors.

[e] First and second lags of explanatory variables are used as instruments in the GMM specification, excluding time dummies.

Table A.3 - EDUCATIONAL MISMATCH AND PRODUCTIVITY ACCORDING TO CSR INDICATOR 2 "MATCHING" (GMM ESTIMATES, CONTROLLING FOR COHORT EFFECTS, 1999-2010)

Dependent variable	Value-added per worker (ln)	
	GMM-SYS[e]	GMM-SYS[e]
Value added per worker (one year lagged, in ln)	0.652***	0.664***
	(0.131)	(0.127)
Required education (one year lagged, in years)	0.048***	0.043**
	(0.017)	(0.017)
Over-education (one year lagged, in years)	0.030**	
	(0.014)	
Over-education among young workers		0.058*
(one year lagged, in years)		(0.035)
Over-education among older workers		0.029*
(one year lagged, in years)		(0.017)
Worker characteristics[b]	YES	YES
Firm characteristics[c]	YES	YES
Year dummies (11)	YES	YES
Adjusted R-squared		
Sig. model (p-value)	0.000	0.000
Hansen statistic	420.4	424.9
p-value	0.90	0.87
Arellano-Bond statistic (AR2)[d]	1.22	1.23
p-value	0.22	0.22
Number of firm-year observations	2,336	2,336

Notes:

[a] Robust standard errors are reported between brackets. ***, **, * significant at the 1, 5 and 10% level, respectively.

[b] Shares of the workforce that: (i) has at least 10 years of tenure, and (ii) is younger than 30 and older than 49 years, respectively. The shares of women, blue-collar and part-time workers as well as the conditional dispersion in hourly wages are also included.

[c] Sectorial affiliation (8 dummies), number of workers, and level of wage bargaining (1 dummy).

[d] AR2 displays the test for second-order autocorrelation in the first-differenced errors.

[e] First and second lags of explanatory variables are used as instruments in the GMM specification, excluding time dummies.

Table A.4 - EDUCATIONAL MISMATCH AND PRODUCTIVITY ACCORDING TO CSR INDICATOR 3 "LT RELATIONSHIP" (GMM ESTIMATES, CONTROLLING FOR COHORT EFFECTS, 1999-2010)

Dependent variable	Value-added per worker (ln)	
	GMM-SYS[e]	GMM-SYS[e]
Value added per worker (one year lagged, in ln)	0.677***	0.691***
	(0.045)	(0.041)
Required education (one year lagged, in years)	0.024***	0.024***
	(0.006)	(0.006)
Over-education (one year lagged, in years)	0.029***	
	(0.010)	
Over-education among young workers		0.040*
(one year lagged, in years)		(0.024)
Over-education among older workers		0.026**
(one year lagged, in years)		(0.012)
Worker characteristics[b]	YES	YES
Firm characteristics[c]	YES	YES
Year dummies (11)	YES	YES
Adjusted R-squared		
Sig. model (p-value)	0.000	0.000
Hansen statistic	489.5	562.0
p-value	0.44	0.26
Arellano-Bond statistic (AR2)[d]	0.98	0.99
p-value	0.33	0.32
Number of firm-year observations	5,489	5,489

Notes:

[a] Robust standard errors are reported between brackets. ***, **, * significant at the 1, 5 and 10% level, respectively.

[b] Shares of the workforce that: (i) has at least 10 years of tenure, and (ii) is younger than 30 and older than 49 years, respectively. The shares of women, blue-collar and part-time workers as well as the conditional dispersion in hourly wages are also included.

[c] Sectorial affiliation (8 dummies), number of workers, and level of wage bargaining (1 dummy).

[d] AR2 displays the test for second-order autocorrelation in the first-differenced errors.

[e] First and second lags of explanatory variables are used as instruments in the GMM specification, excluding time dummies.