

Firm-size wage premiums around the world: Evidence from PIAAC

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An empirical analysis using PIAAC 2013 data

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Abstract

Larger firms pay higher wages. In spite of the large and growing importance of the firm-size wage premium, previous attempts to account for this premium using observable worker or firm characteristics have had limited success. This master thesis reports examine the hypothesis that these higher wages are because workers in larger firms are more skilled. The data used comes from the Programme for the International Assessment of Adult Competencies (PIAAC), which in addition to standard labor information, gives a much richer skill measures than those typically available in labor market surveys. The pattern of firm-size effects on wages is measured with and without this these new controls for worker skill, using the 21-country database. I also investigate the interaction between skill variables and firm-size premium, and the premium differences in the public and the private sector. Firm-size premiums are found universally in every country investigated. The results also show some evidence in that some skills are differently rewarded in larger firms. I also find that, in many countries, firm-size premiums are nonexistent or substantially lower in the public sector compared to the private sector. Last, I find evidence for workers with a higher skill-level sorting into larger firms.

Keywords: Wages, Firm-size, Numeracy, Skills, Public, Private, Efficiency wages, PIAAC

Preface

The thesis is submitted as a requirement for the degree MSc. at Norwegian University of Science and Technology (NTNU).

The data applied in the thesis are cross-sectional data from the Programme for the International Assessment of Adult Competencies survey (PIAAC). Public Use Files have been made available by the Organisation for European Economic Co-operation (OECD) OECD are not responsible for the analyzes/interpretation of data shown in the thesis.

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Chapter 1 Introduction

A large number of empirical studies on individual wage determination report a strong relationship between firm-size and wages. Larger firms pay higher wages. This link was first discovered by Moore (1911) and has been confirmed in later studies (Brown and Medoff, 1989; Oi and Idson, 1999). For example, examining the US, Brown, Hamilton and Medoff, (1990) finds a 35% wage premium for workers in firms with more than 500 employees relative to those in firms with fewer than 25 employees, making the firm-size wage premium as large as the gender-wage gap and larger than the wage differential associated with race and union status. Firms have gotten larger. Over the last 40 years, in countries like the United States, there have been an increase in the number of firms having more than 1000 employees compared to smaller firms with 1-10 employees (SAB, 2016). This give more relevance to examine the firm-size wage effect, also called firm-size premiums.

Many theories have been purposed to explain the origin of firm-size premiums. It may be that larger firms have greater rents to distribute, more often has unions who help workers get a higher wage, or employ higher quality workers, so that the firm-size premiums arise from unmeasured labor-quality. The explanation that larger employers hire better quality workers is considered by some researchers to have more empirical support than any other explanation (Brown and Medoff, 1989). However, Groshen (1991) disputes whether the evidence clearly show that workers sort into different firm sizes according to differences in their human capital. In light of the conflicting views on how worker quality could explain the firm-size wage effect, more evidence is needed.

Most of the previous studies of firm-size premiums have had a limited view of individual human capital or skill level. Often, human capital of an individual is represented by formal education and experience. These are proxies for skill, which rather should be considered as input for acquiring skills. Using the data from the PIAAC¹-survey I have access to cognitive test results of a large sample of individuals aged 16 to 65 in 21 different OECD countries². This give me the unique possibility to examine the sorting of workers into larger firms according to direct measures of skills that are not typically available in labor economics databases. In addition to standard labor force information, I have numeracy score as a direct measurement of cognitive

¹ Programme for the International Assessment of Adult Competencies

² Austria, Belgium, Canada, Canada, the Czech R., Denmark, Estonia, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, Spain, the Slovak R., Sweden, the United Kingdom and the United States.

skill. This survey has previously been used to look at the effect of numeracy on wages. (Hanushek et, al. 2015)

Other research, like Garen (1985), used IQ tests as a direct measurement of cognitive skill. However, the advantage of using the skill measurements from the PIAAC-survey is in contrast to IQ test and, for example, military recruits cognitive test, that these often are not done at the same time as observing an individual's actual wage. Moreover, they may capture skills that are mainly unrelated to a work setting. Gibson and Stillman (2009) used literacy test scores from the International Adult Literacy Survey (IALS) to examine firm-size premiums. The PIAACsurvey gives me access to more recent, more comparable cognitive skill test scores and data from a larger sample of countries, than Gibson and Stillman (2009) had access to.

The plan of action in this master thesis is to use new, richer and more comparable measure of cognitive skills to estimate whether firm-size wage premiums persists after controlling for factors that previous studies have treated as latent. If the firm-size premium decreases when these new variables are introduced, it suggests that part of the wage effect, which previously have been attributed to firm-size, may just be due to unmeasured differences in labor-quality. The firm-size wage effects are examined over 21 different OECD countries and compared to each other.

I will study previous research of firm-size premiums and human capital and examine what lie behind their choice of models and which specifications that best suit my model for estimating firm-size premiums. An interesting extension is to examine if education and the test scores from the PIAAC-survey is rewarded differently in larger firms. Another extension is to compare the differences of firm-size premiums in the public and the private sector. The wage system in the public sector is often more rigid and less flexible than in the private sector.

The thesis is structured in the following way:

In chapter (2) I will describe the different explanations for firm-size premiums and a human capital model, which I extend with a direct measurement of cognitive skill. I will tie these together to a model used to test the hypothesis of firm-size premiums being a result of unobserved labor-quality. In chapter (3) I will present previous research on firm-size premiums and the return of skills. Chapter (5) will contain a description of the data and variables used in my estimation. In chapter (6), I will present my empirical results.

2

Chapter 2 Theory frame

In this chapter I will look into models and theories explaining how and why firm-size premiums may arise in different countries. First I will start with a brief overview of the different theories behind firm-size premiums, then I will look more closely at the model for efficiency wages, focusing on shirking. I will also examine a human capital model, which explains the relationship between human capital and wages. I will use this to look at how firm-size premiums may change when taking into account different variables for human capital.

2.1 Firm-size Premium

Larger firms pay higher wages. This link was first discovered by Moore (1911) and has been confirmed in later studies. Davis and Haltiwanger (1991) show that, in the US, the gap in real hourly wages between production workers in firm with 20 to 49 employees and production workers in firms with more than 5,000 employees increased by 79% between 1963 and 1986. Suggesting either that large firms have different ways of rewarding 'equivalent' workers, or equivalent workers exhibit 'different' behaviors in large firms. However, most of the evidence for firm-size wage effect uses either individual survey data, with limited information on firms, or firm survey data, with limited information on individual workers. These approaches potentially suffer a serious omitted variables problem. (Belfield and Wei, 2004)

In what follows, I give a brief account of the existing theories from Belfield and Wei (2004) regarding firm-size premiums.

Skill and technology complementarity:

Employees with a higher skill level will be paid more, and larger firms may need to hire more skilled employees. If these skills are hard to observe or control, a firm-size premium would emerge (Garen, 1985). Employers may also find it profitable to match high-skill workers with other high-skill workers, and this matching could lead large firms to hire only high-skill workers (Barron, Black, and Loewenstein, 1987). It could be the case that large firms offer more specialized training, spread of intra-firm skill, and a greater specialization of tasks (Rebitzer and Taylor, 1995; Dunne and Schmidz, 1995). Another example; larger firms may choose more capital-intensive and efficient methods and higher utilization rates, like multiple shifts (Idson and Oi, 1999). All these variables are hard to measure fully. Yet, productivity appears to be negatively related to firm-size (Haltiwanger, Lane and Speltzer, 1999). Main and Reilly (1993) find a small wage premium for skilled employees in large firms, although general controls for

skill composition and capital-labor ratios do reduce the firm-size premium, a sizeable premium remains (Troske, 1999). Gibson and Stillman, (2009) uses literacy test scores from the International Adult Literacy Survey as a control variable. The results show that the firm-size premium is not as universal as is often suggested, but in countries where it exists controlling for literacy skills does little to reduce the size of these premiums. The PIAAC data represents a unique possibility to test the hypothesis that firm size premiums reflect unobserved labor-quality. The data covers a larger number of countries with 21 OECD countries, and are more recent than the data used in Gibson and Stillman (2009)

Compensating wage differentials for job characteristics and fair pay:

Workers may be paid more as a compensation for less desirable or congenial working conditions (holding skill constant). These conditions may be found more frequently in firms with a large number of workers, e.g. in factories. If so, this relationship would cause a wage premium. However, the general evidence is that smaller firms offer worse working conditions, such as higher accident rates (Wagner, 1997). Evidence of whether workers in smaller firms have higher job satisfaction is also inconclusive (Clark, 1996). Consequently, introducing controls for working conditions in past studies has not reduced the firm-size premium significantly (Brown and Medoff, 1989).

Akerlof and Yellen (1990) suggests that the effort of the workers depends on the wage they receive relative to their perception of a fair wage. If workers get the wage that they deem fair they provide a normal work effort (Akerlof and Yellen ,1990). However, if the wage is lower than the fair wage workers will provide less than what is considered normal work effort. Minimum wage is in this case intended to mean the wage that workers perceive as fair. Akerlof and Yellen (1990) mentions a real incident that illustrates the theory of fair wages, "in 1982, when General Motors negotiated wage concessions with its union employees and thereafter announced bonuses for its executives, the loss of morale amid the ensuing uproar forced retraction of the proposed bonuses. GM and the UAW subsequently negotiated an equality of sacrifice agreement that required white-collar and blue-collar workers to share equally in reductions or increases in pay. Demands for wage cuts for workers therefore lost all credibility, and was perceive as fair pay is uncertain. Akerlof and Yellen (1990) suggests that workers are using reference groups to compare their wages with wages of workers in similar occupations within the enterprise, or by comparing themselves with similar workers in other businesses. In

the incident with General Motors and the United Auto Workers, the fair wages were influenced by the management's dealings and bonuses.

Union organization and bargaining power

Unions may be able to form and bargain more effectively in large firms. From the theory of efficiency wages, these unions may be able to bargain mutually beneficial changes to wage contracts, which raises overall productivity (Akerlof, 1982)

The firm-size premium may therefore be a proxy for the union wage gap (Miller and Mulvey, 1996). However, unions may reduce the firm-size premium if they compress the upper bound on wages (Pearce, 1990). Green, Machin and Manning (1996) finds the firm-size premium to be three times higher in the non-union sector compared to the union sector. Firms may be willing to pay efficiency wages as this can prevent the creation of a trade union in the enterprise (Katz, 1986). The problem with unions seen from the corporate side is that depending on the power it has, it often has demands that the firm either doesn't want to agree to or possibly cannot accept. If this is the case, they face a possible strike. The consequence of this is, at worst, that the production halt indefinitely. To avoid such incidents, the firms can choose to pay an efficiency wage that is sufficiently high enough for the workers to not have an incentive to create a union. Dickens (1986) proposes that companies can avoid the creation of a union by paying the same wages as the workers would receive under collective bargaining minus costs related to running the union. To accomplish this, the company can compare the wage paid for comparable workers in other companies where there is a union present.

Managerial skills and better work organization

Skilled managers have a comparative advantage in managing the firm rather than in monitoring workers, so they prefer skilled workers who need less supervision (Oi, 1983). They may also be more likely to adopt performance enhancing strategies, such as performance related pay (Addison, Siebert, Wanger and Wei., 2000). Larger firms controlled by skilled managers may employ more sophisticated capital, like new technology, because larger firms have larger output over which to amortize the fixed costs of technological upgrading, and skilled workers are complementary to computers and other types of knowledge-demanding capital (Dunne and Schmitz, 1995). However, it is not clear why such managers would share their rents with other workers.

Market powers, profits and rent sharing

Market power is strongly correlated with firm-size (Akerlof and Yellen, 1990). In industries with less competitiveness, firms are more likely to generate higher rents (profits), and they may share these higher rents with their employees. However, it is not clear how or why such rentsharing occurs (Dewhurst and Burns, 1983; Dobson and Gerrard, 1989). There is good reason to argue that companies that earn high profits may be willing to share some of their profits with the workers. After all, it is much to gain from having a happy and cooperative workforce. From this there is a potential link between the rent-sharing and the theory of efficiency wages. It may therefore be in the company's own self-interest to engage in rent-sharing since much potential profit could be lost if workers are unhappy. Thus, it is possible that a union does not necessarily need to push the company to share profits with the workers, but it could happen on a voluntary basis from the company's side. Whether workers receive a share of profits by having a trade union and collective bargaining or by rent-sharing is an important question of whether it is really so that the profits of the enterprise are involved in determining the size of workers' wages. Blanchflower Oswald and Sanfey. (1996) estimates of US data, find that wage premium with respect to profit, after controlling for human capital, is 0.08. Lester (1952) "range of pay" is defined as the difference in wages for equal workers, from the company with the highest profit to the company with the lowest and comparing this with the average wage. Blanchflower et, al. (1996) estimated Lester's "range of pay" to be 24%. This in turn suggests that the variation in wages for equal workers as a result of variation in profit amounts to approximately one quarter of the average wage. Using observations from the United Kingdom, Hildreth and Oswald (1997) estimates Lester's "range of pay" to be 16%, while Arai (2003), from Swedish data, estimates it to be between 12% and 24%. These publications document to some extent that there is a positive and real connection between profits and wages.

Internal labor markets and hiring

Employee wages depend on how well their skillsets match their jobs, and large firms may be able to match employees more efficiently. This sorting may occur through the hiring process (Devine and Kiefer, 1993; Siebert and Addison, 1991). Alternatively, it may occur either via imperfect information about where the high-paying jobs are (Green et al., 1996); or via degrees of work stability, with smaller firms offering more unstable employment prospects (Mayo and Murray, 1991; Winter-Ebmer, 2001). Better matches can also occur when firms reallocate workers, which may be easier in larger firms (Green, 1988; Abraham and Farber, 1987). This

effect may be durable, in that job matches within the workplace cannot easily be arbitraged away (by competition from the pool of workers not employed at the workplace).

Tradeoff between monitoring costs and pay

Monitoring workers to ensure high productivity are more difficult and therefor costlier the larger the firm is. Firms may pay workers a higher wage to encourage workers to be productive and not shirk, and with that reducing supervision cost (Shapiro and Stiglitz, 1984). This theory has received a lot of attention, although it is not supported by evidence on non-managerial workers in Green et al. (1996) and Troske (1999).

Next I will examine how the theory of efficiency wages and shirking and may explain, to some degree, why larger firms pay a higher wage.

2.2 Efficiency wages

The theory of efficiency wages is based on the idea that it may be in the company's own interest to offer a wage that is higher than the market set wage. It must thus be advantages associated with offering higher wages, and these benefits must outweigh the extra labor costs. The proposed benefits by offering higher pay than needed include; less "shirking" (do less work than agreed, skipping work), get better qualified workers, less likely to lose important labor, have higher morale, loyalty and discipline among the workers. These benefits give the assumption that there is a correlation between wages and productivity / efficiency, hence the name efficiency wages. I will present how efficiency wages are more useful for firms the larger the firm is.

Wages and Productivity

The theory of efficiency wages proposes that there is a correlation between wages and productivity, namely that the productivity of a worker increases with higher wage. Katz (1986) assume identical firms in a competition market where all firms in the short term, which have the following production function:

$$Q = aF(e(w)L) \tag{2.1}$$

(*L*) represents the number of workers in a firm. (*e*) is efficiency or work effort of the worker, (*w*) is real wages, (*a*) is a measure of the technology business, and (*Q*) is the produced quantity of the firm. It is believed that all workers have an identical efficiency function given by (e(w)), (where e' > 0 and e'' < 0). The work performed by workers increases with higher wages, but at a diminishing rate. Furthermore, it is assumed that the price of goods is normalized to one, and that companies are able to hire as many workers as they wish, regardless of the wage they offer. Firms maximize the following profit function:

$$\max_{w,L} [\pi = aF(e(w)L - wL]$$

$$\frac{\partial \pi}{\partial L} = aF'(e(w^*)L)(e(w^*)) - w^*$$

$$aF'(e(w^*)L)(e(w^*)) = w^*$$

$$\frac{\partial \pi}{\partial w} = e'(w^*) * \frac{w^*}{e(w^*)} = 1$$
(2.2)

The optimal wage (w^*) satisfies the condition that the elasticity of effort with respect to the wage is unity. The wage (w^*) is known as the efficiency wage since it minimizes wage costs per efficiency unit of labor. Each firm hires labor up to the point where its marginal product equals labor cost. The intuition behind the optimality condition is that when marginal product of labor is greater than the wage, the worker's contributions outweigh the costs and it is therefore beneficial for the company to employ the worker. However, if the wage is greater than the marginal product the wage, the cost for the firm will be greater than the worker's contribution and a company will thus lose money by hiring the worker.

Even if the wages are raised over the initial marginal cost it is not guaranteed that the firm is worse off. This is because the higher wage leads to more effective workers which in turn results in a higher marginal product. It can therefore be worthwhile for the company to raise wages if the marginal product sufficiently increases.

Firms may be reluctant to use the opportunity to get lower labor costs by firing workers when the market changes to a new and lower equilibrium, for example as a result of an increased supply of labor. The reason that firms do not like to utilize the option, is because the gain of reducing labor costs does not outweigh the negative effect reduced wages have on the productivity and morale of workers.

When productivity is determined by the wage of workers it is optimal to offer efficiency wages. After all it is efficiency wages that theoretically offers the firms the highest revenue. Borjas (2010) comments the following: "Because different firms have different effort and production functions, different firms may choose two different pay efficiency wages". In other words, by removing the assumption that all firms have a similar product functions and efficiency functions, businesses will be able to set different efficiency wages. For example, (e(w)) will vary for different companies. Thus, efficiency wages will be highest in those companies where the relationship between wages and productivity is strongest.

2.2.1 Shirking

If workers dislike exerting a high effort at work, and the employer cannot effectively observe what they are doing at any given time, which is harder the larger the firm is, the workers can have an incentive to shirk. Because even if a worker is caught shirking, it is not associated with any costs or real punishment. The firm's possibilities when it comes to punish workers who shirks are limited. Katz (1986) describes this as follows: "Firms can suspend, demote, or fire an employee for inadequate performance or misbehavior, but imprisonments, physical torture, direct cash fines, or resort to tort or contract law for redress are simply not available options for many forms of worker malfeasance ". The company can thus fire a worker, but the problem is that in a labor market characterized by perfect competition a worker will immediately get a new job. A job which furthermore pays the same wage as the previous one. It is assumed here that there are no costs attached to finding a new job. This assumption follows that when workers are identical, the companies will assume that everyone has an incentive to shirk. Katz's point is that the possibility to fire an employee dose not "scare" the other employees. This is of course disadvantageous for the firm

Additionally, it is difficult and costly to catch employees shirking, due to imperfect information about the employee's effort. The problem with workers who shirk, is that it cannot be solved by paying a pure productivity wage, a wage that is determined by the individual's production output.

The cost of shirking is two-sided for the firm. Firstly, there are cost related to workers not providing a satisfactory effort in the workplace, and secondly, there are significant costs associated with having to monitor workers. If firms have imperfect information about whether the workers are doing their job, they cannot observe workers' individual work effort and productivity to a perfect degree. From this, firm will have a incentive to pay a wage that exceeds the market set wage. Shapiro and Stiglitz (1984) formalizes the theory in a model that explains in more detail what factors can make various companies choose to set different efficiency

wages. In the model, there are (N) number of risk neutral and utility-maximizing workers, where all of these have a utility function given by:

$$U = w - e \tag{2.4}$$

There is a positive utility for the workers to consume goods and services and this can be acquired through the wage they receive, given by (w). This wage has to be acquired by exerting effort, given by (e), which reduces the positive utility. The workers could either exert minimal effort: (e = 0), or a exogenously given positive effort: (e > 0). If the workers are unemployed they will receive unemployed benefits, given by (\overline{w}). There is a probability (b), per unit of time, that workers will lose their jobs. This parameter is exogenously given and can be described as every conceivable explanations for why a worker could lose his job other than shirking. For example, by quitting or downsizing in the company.

The only decision the workers makes in the model is to choose whether to work to their fullest capacity or not (shirking). A worker selects the level of effort on the basis of which of the two options that maximize the utility for the worker. (V_e^n) is defined in the model as the expected utility during a lifecycle of a worker who does not shirk, while (V_s^n) is defined as the expected utility during a lifecycle of a worker who shirks. (V_u) is the expected utility during a lifecycle of a worker who shirks. (V_u) is the expected utility during a lifecycle of a worker who shirks. (V_u) is the expected utility during a lifetime for an unemployed worker. Unlike Shapiro and Stiglitz I choose to set up the model in discrete time, rather than continuous time. This is also done by Netteland (2011). Making the model, especially initially, more comprehensible, while the main result is changed to a small extent.

Expected utility for the worker who does not shirks at work is given by the following equation³:

$$V_e^n = w - e + \frac{b}{1+r}V_u + \frac{(1-b)}{1+r}V_e^n$$
(2.5)

Equation (2.5) illustrates the positive utility of the wage received and the negative utility given by exerting effort, for a worker that does not shirk. In the next period the worker either lose or quit their job as a result of exogenous causes, given by the probability (*b*), or keep their job, given by the probability (1 - b). Whatever the outcome, the current expected utility discounted at the worker's utility discount rate given by (*r*). Solving Equation (2.5):

$$V_e^n = \frac{(w-e)(1+r) + bV_u}{r+b}$$
(2.6)

³ Please see appendix for full link between the equations.

Equation (2.6) indicates the value of the expected utility over a life cycle, for a worker who does not shirks at work. From the equation it is clear that the expected utility is increasing in wages and in the chance of losing their job. While it is reduced by a higher effort. It can also be shown that the expected utility is reduced by a higher utility discount rate or by a higher probability of losing their job by exogenous causes.

Expected utility if the worker shirks is given by:

$$V_e^s = w + \frac{b+q}{1+r}V_u + \frac{(1-b-q)}{1+r}V_e^s$$
(2.7)

The difference from equation (2.5) is that the worker who shirks does not provide positive effort and therefore does not have reduced utility as a result. However, the worker has a greater chance of losing his job. Solving equation (2.7) I get the following expression for the expected utility for the worker who shirks at work

$$V_e^s = \frac{w(1+r) + (b+q)V_u}{r+b+q}$$
(2.8)

For the workers to exert positive effort the following condition: ($V_e^n \ge V_e^s$), must hold. The expected utility of not shirking at work must therefore be greater or equal the utility of shirking at work. Shapiro and Stiglitz call this condition: "the no-shirking condition" (NSC). It is assumed here that if the utility of the two options are similar, the workers choose to provide a positive effort and not shirk. By solving the condition in equation (2.8) for (w) I get the wage required to enable the worker to choose a positive effort:

$$w \ge \frac{r}{1+r}V_u + \frac{e(r+b+q)}{q} = \widehat{w}$$
(2.9)

Note that the critical wage (\hat{w}) is positively related with effort level (e), the utility of being unemployed (V_u) , the discount rate (r) and the quit rate (b), but is inversely related with the probability of being caught shirking (q). Equation (2.9) indicates the efficiency wage as needed for the NSC condition to hold.

If we remove the assumption that all firms are identical, it could explain how companies in different degrees can choose to take advantage of efficiency wages. Equation (2.9) tells specifically what determines the optimal efficiency wages. Increased utility associated with being unemployed, given by a bigger (V_u) , makes the cost linked to being unemployed lower and the wage must increase to make up for this. A higher utility discount rate (r) results in an

increase of the optimal efficiency wage. This is explained by that at a higher discount rate, workers add more emphasis on the immediate future and in the short-term gain by shirking, relative to the expected utility loss in the future when the worker eventually loses their job.

Optimal efficiency wage increases with the positive value of effort. This is because the higher value of (e), the lower utility the worker gets. This follows form the worker dislikes working and the incentives to shirk has thus gotten larger. Wages must increase to compensate additional discomfort of higher expected effort. If the probability of losing their job, by exogenous causes increases, given by a higher (b), then the optimal efficiency wages also have to increase. This explained by the likelihood of being terminated is so great, workers can just as easily fail to provide a satisfactory effort. Finally, it leads to a lower probability of being caught shirking at work. I will now look at the implications these factors have on firm-size premiums.

$$q = q(firmsize), q' < 0 \tag{2.10}$$

Where (q) is the probability of getting caught shirking, (q) is a function of firm-size. The larger the firm, the more difficult it is to monitor workers. This leads to a lower the probability for the worker to be caught shirking.

Following this the optimal efficiency wage increases. It is intuitively that if incentives to shirk has increased, efficiency wages must compensate for this. Assuming that firms in the model are heterogeneous, this entails that the values of (b), (q) and (e) will vary from company to company. If, for example, the probability of losing their jobs by exogenous causes vary for different companies, this will according to equation (2.9) mean that companies set different efficiency wages among themselves.

Summarized: From the worker's point of view, he or she wishes to keep a high remuneration because entering into unemployment represents a penalty given by the loss of the high wages themselves and because with high salaries the labor demand will be low, which implies long spells of unemployment. As a result, to keep the same level of labor income, workers will choose to devote the highest amount of effort necessary to reach the critical wage at NSC.

From the firm's side, when they have control over their monitoring technologies, two outcomes are possible. Firms that face high monitoring costs will have incentive to pay at least (\hat{w}) as a worker discipline, and also because they want to keep a high level of output due to increased effort. But if the monitoring costs aren't high enough, the firms do not need to pay an elevated

salary because they can easily observe worker's effort and this is a sufficient mechanism for no-shirking. Another way efficiency wages could be beneficial for the firm is that it could reduce hiring cost. Since higher wages should decrease employee turnover, the firm has to spend less on hiring and training replacement workers. Table (1) gives an overview of the different theories regarding efficiency wage.

Theory	Problems leading to efficiency wage payments	Benefits to firm of high wages
Shirking	Imperfect observability of worker effort level and performance, monitoring is costly. Harder to observe in larger firms	Raise cost of job loss encouraging good performance; economize on monitoring costs
Turnover	Firms must bear part of turnover costs (hiring and training costs)	High wages reduce turnover costs if quit rate is decreasing function of wages
Adverse selection	Imperfect observability of worker quality and performance. Harder to observe in larger firms	Attract higher quality pool of applicants if more productive workers have better outside opportunities
Sociological	Morale and worker feelings of loyalty to firm depend on perceived fairness of wages. Harder to give non-monetary positive feedback to workers and unity in larger firms.	Improved work norms, morale, feelings of loyalty to firms which raise productivity
Union threat	Costs of replacing existing workforce gives employees bargaining power. Larger firms has a higher probability of workers unionizing	Maintain industrial peace or prevent I unionization

Table 1 A synopsis of alternative efficiency wage theories. Source: Katz (1984)

The theories discussed above have all been tested to some extent, but two important questions remain unresolved. First, what is the relative explanatory power of each theory? Second, are these theories together sufficient to explain the firm-size premium? Next I will look at an econometrical model using human capital to examine firm-size premiums

2.3 Human capital model

As stated above the firm-size premium may come from the hypothesis that larger firms attract higher skilled workers, worker with higher "human capital". The composition of the workforce of a company naturally affects the average wage. Variables such as education, experience and seniority is positively correlated with the wage of each worker. In this chapter I will look at models and theories explaining how education, experience and skills affects individuals' income. I will first start with a simple human capital model, first formulated by Mincer (1974), which explains the relationship between education and income. Most of the recent studies of human capital influence on wage is rooted in Mincer's Human Capital Earnings Function (HCEF). According to this model, the logarithm of an individual's income in a given time period decomposed into a function of education and work experience squared.

$$logy_i = \alpha_i + \alpha_1 S_i + \alpha_2 X_i + \alpha_3 X_i^2 + e_i$$
(2.11)

Where $(logy_i)$ is the logarithmic individuals earnings. (S) is the number of years completed education and (X) is the years of experience after education is completed. While (e_i) is a stochastic error term. This forms the basis of human capital theory. An individual's income is a function of the individual's human capital. The more and better qualities the individual possesses, which are valued in the labor market, the higher the human capital and from this the higher the income the individual will get. Mincer assumes implicit that education is the only systematic source for variation is skills. Although Mincer developed this equation from a theoretical model about choice of education and training after school, the pattern in HCEF appears to explain much of the return of education or if individuals who has higher wages choose more education because of factors like higher ambition and academic skills

Income measurement: In human capital theory, the income function is analyzed by a number of different objectives: Yearly income, monthly salary or hourly wage, but almost always in logarithmic form. The logarithmic form has several fortunate properties: The distribution is almost a normal distribution, a close linear relationship with education, and it is convenient for interpretation (Hanushek, Schwerdt, Wiederhold and Woessmann., 2015). Individuals with higher education tend to work more than individuals with lower education, meaning return of education will seem to be greater with the measurements of weekly, monthly, or annual salary. When hourly wage is used as the dependent variable, the focus will be on productivity or the

valuation of the worker's abilities in the labor market and thus provide a clearer measure of individual differences in human capital.

Education measurement: In Mincer's HCEF it is assumed that the logarithm of the wage is a linear function of the number of years completed education. There are two key assumptions that underlie this specification. These are the best measurement of education is the number of years of completed education and every additional year of education has the same proportional effect on income. Under these assumptions coefficient (α_1) will in equation (2.11) give the full effect education has on income in the labor market. Assuming as well that education is free and that students do not earn anything during training, (α_1) may interpreted as the return of an investment in education.

2.4 Signaling

In markets with biased information we could get equilibria with "adverse selection"⁴. Until now I have assumed that education provides properties that are valued in the workplace. Employers cannot observe all these characteristics. Individuals with lower productivity would therefore try to hide this. Similarly, therefore, individuals with higher productivity wish to signal this to the employer. This can be studied further using an example from Varian, (1992, p. 727). We start with two types of workers with productivity(marginal product) (a_H) and (a_L). Where ($a_H > a_L$)⁵. The productivity is unobservable by the employer and they work the same amount of time. Therefore the employer cannot distinguish between which is more productive. The expected average wage is then:

$$w_P = (1 - b)a_L + ba_H \tag{2.12}$$

$$a_L < w_P < a_H \tag{2.13}$$

Meaning that a more productive worker is paid less than their marginal productivity while the lower productive worker is paid more. The "good" worker then has an incentive to signal their productivity.

A possible way to signal productivity is using education. We assume that education has no impact on the productivity of workers, but employers will prefer higher educated individuals as these tend to have higher productivity. It is natural to assume that it is less costly for the more

⁴ Asymmetric information between the parties

⁵ a_H – High productivity, a_L – Low productivity

productive to study. The cost of taking *e* years of education can be presumed to be, $(c_L e)$ and $(c_H e)$ for the low productive and the high productive worker, repsectivly. Where $(c_L > c_H)$ Workers expect a wage w(e), where *w* is an increasing function of education *e*. Using e_L and e_H as the education level which the two groups choose, an equilibrium must satisfy the following conditions

$$w(e_L) = a_L$$

$$w(e_H) = a_H$$

$$w(e_L) - c_L e_L \ge w(e_H) - c_L e_H$$

$$w(e_H) - c_H e_H \ge w(e_L) - c_H e_L$$

$$(2.15)$$

Equation (2.14) display the wage as a function of education given the different education levels. Equation (2.15) displays the "self-selection" condition. Showing that is it is more beneficial to choose the education level suitable for their productivity group. If the education payoff is the same for each group, the signaling would not work.

In the above example, it is assumed that education only acts as a signal output and does not increase workers' skills. This is of course an unrealistic assumption, but it gets evident theory first formulated in Spence (1973). Spence argues that a hiring process is an uncertain investment by the employer. The greater the chance for the worker to be good, the more they are willing to invest in the form of wages. Thus, workers signal that they are skilled through higher education. This signaling theory point in the direction of exciting effects that should be taken into account in human capital models. The number of years of education is not necessarily the best measure of the human capital an individual possesses.

Several economists have argued that a degree means more than the number of years of schooling. That there is a wage premium for completing an ongoing education. This theory is called the Sheepskin effect. Card and Krueger (1992) found particularly a non-linearity between education and income by 15 to 16 years of schooling, that is, by completing college in the American school system. Lemieux (2006) found that the linear function explains co-relationship between education and logarithmic income well except at very low levels of education. He argues that the linear approach fits well in stabile economies where growth in relative demand is offset by growth in relatively supply. Perhaps the Mincer function was proved to be too successful, so scientists have ignored important questions regarding the

assumption that education is the only systematic source of skill differences? (Hanushek et al., 2015)

2.5 Directly observable cognitive skill

What the PIAAC survey makes possible is to follow an alternative approach built on the direct measurement of cognitive skills. I want to examine how skill scores can give a clearer picture of an individual's human capital. In this thesis I will use direct measures of cognitive skills. Standardized test results are used to measure skills. If these skills capture all variation in human capital, (*H*), then the test results may be used directly in the simplest human capital model in equation (2.11) as a measure of human capital. It is unlikely that cognitive skills capture all the relevant variation in individuals' human capital. Therefore, the test result (*C*), can be seen as a measure of human capital (*H*), which may contain a measurement error, (μ) (Hanushek et al. 2015)

$$H_i = C_i + \mu \tag{2.16}$$

$$y_i = \gamma H_i + \epsilon_i \tag{2.16.1}$$

Where (y_i) is the individuals wage and is a function of the individuals human capital (H) and a stochastic error term (ϵ_i) . Estimating the equation with only skills as a measure of human capital there will occur a measuring error, if the skills do not capture all variation in human capital. With this model it can thus be expected that there is a bias in the estimate so that (γ) will be skewed toward zero. With the inclusion of skills in Mincer equation from equation (2.11) it is likely that skill score, (C), is correlated with the number of years of education, (S), since better skills will lead to increased schooling through a reduction in the marginal cost of education.

$$\log y_{i} = \alpha + \alpha_{1}C_{i} + \alpha_{2}X_{i} + \alpha_{3}X_{i}^{2} + \alpha_{4}S_{i} + e_{i}$$
(2.17)

Thus, (α_1) could have a positive bias, although (S) does not have any effect on income other than through (C). These models suggest that it can be expected bias in the estimate and the coefficient for (C) will be a lower limit for the effect of human capital on income (Hanushek et al., 2015)

Green and Riddell (2001) expands Mincer model using skills as an explanatory variable, and also takes into account that some skills are observable and others are not. They argue that one must look at education as an input that increase skills and thus human capital, rather than looking at it as a direct measure of human capital.

To examine my topic question I will use equation (2.17) and reform and expand it with firmsize dummies.

$$lnwage_{ijc} = \alpha_c + firmsize_j\theta_c + numscore_i\omega_c + education_i\pi_c$$
(2.18)
+ experience_i^2\varphi_c + experience_c^2 + u_{ijc}

The model consists of four firm-size dummies, representing the different firm-size categories given in the PIAAC-survey. The skill score is represented by the numeracy score for individuals in the survey. Number of year of education and experience is provided by the individual survey takers.

Summary: There are many explanations for the firm-size premiums, as discussed above. In this chapter I have argued that when testing how skills effects firm-size premiums it is relevant to use several proxies for this wide term. It is very useful to have direct cognitive skill test results, but it is also useful to include more traditional variables when trying to tie skill to the firm-size premium. The classic Mincer model for human capital effect on income is both successful and popular, but as mentioned, there has been much discussion around what is a good measure of human capital. Number of years of schooling is the most common measure, but it is several factors and theories that suggest that this gives a distorted picture of individuals' human capital. By having data on individual test results on cognitive skills gives me a much more nuanced picture of human capital and a unique opportunity to both expand and test the relevance of the classic Mincer model and classic studies on human capital when looking at the firm-size premiums often observed.

Chapter 3 Previous research

In this chapter I will present a number of previous studies on firm-size premiums and the return of skills.

3.1 Firm-size premiums

How the size of firm or establishment explains the wage differentials between employees of similar characteristics is not a new question in labor economics. This phenomenon has been studied for several decades and researchers have provided evidence of strong and positive effect of size of employer on wages of employees. Such studies include Moore (1911), Lester (1967), Brown and Medoff (1989), Brown et al (1990), Idson and Feaster (1990), Oi and Idson (1990), Groshen (1991), Main and Reilly (1992) Mizala and Romaguera (1998), Troske (1999), and many others. Yet the answer to why large employers pay more is largely unexplained. Many empirical studies have shown a strong and positive relationship between employer size and wages.

Brown and Medoff (1989) tested six hypotheses to explain the relationship between employer size and wages: Large employers (1) employ higher-quality workers, (2) offer undesirable working conditions, (3) pay for union avoidance, (4) have a stronger ability to pay high wages, (5) face smaller pools of applicants relative to vacancies or (6) are less able to monitor their workers. These authors have presented two observations. First, large employers pay more for their labor but less for their other inputs because of lower interest rates on funds and quantity discounts. Second, large firms are also older firms and perhaps the employer size-wage may actually be a relationship of firm age and wage. After controlling for union status, education, experience, seniority, industry, region and profession, working at different-sized employers with the size of one employer being double the size of the other, the individual working for the larger employer receives a wage premium of 1.5 to 3.8%.

In the United States, Brown et al. (1990) reported 35% higher hourly wage in firms with 500 or more workers. Groshen (1991) found, after controlling for occupations, establishment wage differential variation from 12 % in the cotton and manmade textiles industry to 58 % in the industrial chemicals industry. Similarly, Stephen and Melissa (1997) found 18 % and Mizala and Romaguera (1998) reported 7 to 9 % of individual wage variation due to establishment wage differentials. Several strategies have been used to account for the unobserved heterogeneity among employees when estimating firm-size wage effects. Evans and Leighton

(1989) used Panel data studies that control for individuals fixed effects. Another strategy used is "matched employer-employee" data, which allow skill measures for each plant to be included in the wage equation for individual workers. This variable allows a test of whether skilled workers actually sort into larger firm, and shows the impact on firm-size premiums when skill measurement variables are added to the wage function.

Troske (1999) uses a matched employer-employee dataset with US observations to examine the different explanations closer, and finds evidence for two of the total of seven theories. 45% of the wage premium associated with firm-size can be explained by these firms having more capital per worker, while 20% of the wage premium is a result of large businesses employing more highly qualified workers. The results of many recent studies are also consistent with the previous studies. For instance, Paez (2003) found that large firms offer on average 3.3% higher wages than small to medium size firms in Colerado, US. Main and Reilly (1993) showed the existence of a wage gap of around 18% between large and small firms in the United Kingdom.

Albæk, Arai, Asplund, Barth and Madsen (1998) finds firm-size premium results for Scandinavian countries, which are in line with previous research on the subject for other countries. The firm-size wage premiums they obtain are, in contrast to other dimensions of the wage distribution, comparable to the firm-size premiums in other countries such as the U.S. with completely different institutions of wage setting. They investigate the consequence of measurement error associated with the common practice of using midpoints of firm-size classes to estimate the firm-size wage premium. The results indicate that using size–class midpoints essentially yields the same results as using exact measures of firm-size. Using firm-size dummy variables and comparing the 1000+ employee firm-size category over the 1-9 employee category they find firm-size premiums to be: 12% for Denmark, 9.1% for Finland, 20.6% for Norway and 13.5% for Sweden.

Lallemand, Plasman and Rycx (2007) examined the magnitude and sources of the establishment-size wage premium in five European countries; Belgium, Denmark, Ireland, Italy, and Spain. They used a unique harmonized matched employer–employee data set, i.e. the 1995 European Structure of Earnings Survey. This survey contains detailed information, reported by the management of the establishments, both on the individual workers (e.g. gross hourly wages, bonuses, age, education, tenure, sex, occupation) and the employers' characteristics (e.g. sector of activity, region, level of wage bargaining, size of the establishment). Interestingly, the size of the establishment is measured by the exact number of employees. They show the existence of positive and significant firm-size premium in all

countries, even when controlling for human capital variables, occupations and gender. These premiums derive partly from sectoral effects (in all countries), size differences in working conditions (in Spain, Denmark, and Italy), regional effects (in Spain), and size differences in levels of wage bargaining (in Belgium and Spain). After controlling for a number of explanatory variables, doubling the size of the firm is associated with a wage premium of 3% in Belgium, 0.6% in Denmark, 3.9% in Ireland, 4.5% in Spain and 3.3% in Italy.

Gibson and Stillman (2009) is very much in line with the research presented in this study, but uses a different data set. They base their study on The International Adult Literacy Survey (IALS), which applied a standardized questionnaire to adults in nine OECD countries, beginning in 1994: United States, Canada, United Kingdom, Germany, Switzerland, Belgium(Flanders), Ireland, Poland and New Zealand. In each country, the survey was based on a probability sample and was designed to be representative of the civilian, noninstitutionalized population aged 16-65 (OECD, 1997). Together with the data collection the survey participants participated in a 45-minuite test hat assessed individuals' literacy levels in their workplace and in daily life in terms of prose, document, and numeracy literacy. In addition to collecting data on literacy, standard human capital and labor market data were collected, including a question on firm-size. Their data consisted of four firm-size dummy variables:1-19, 20-99, 100-500 and 500+ employees. Their results show that firm-size premiums are not as universal as is often suggested. However, in the countries where they do find a significant premium, their findings do not support the hypothesis that the widely observed firm-size premiums reflect differences in unmeasured labor quality. Controlling for both education and workplace literacy has no qualitative impact on the firm-size premiums in any country that has a statistically significant premium. They analyze the wage differences in the different firm-size categories and find a 10.7% to 48.7% higher wage for employees in 500+ employee firms compared to employees in firm with 1-19 employees. With the highest being in Canada and the lowest in Belgium. United states and the United Kingdom had a 22.7% and 20.6% premium in the largest firm-size category, respectively.

3.2 Return to skills

The issue of question is to test the hypothesis that firm-size premiums arise from skilled workers sorting into larger firms, and their higher than average skill-level is rewarded. There has been a lot of studies looking at how skills or human capital is rewarded.

Murnane, Willet and Levy (1995) examines the extent to which the importance of cognitive skills has changed in recent decades by comparing how math skills of high school seniors affects their wages six years after graduation. They investigate whether the increased demands at work due to development in industry and services has led to changes in the skills of the students, and if cognitive skills have become more important in wage determination now than earlier. They use data from "The National Longitudinal Study of the High School Class of 1972" (NLS72) and "High School and Beyond" (HS&B) which contains data for individuals who have completed formal education in 1972 and 1980, respectively, and is employed 6 years later. By examining the relationship between logarithmic hourly rate and test scores in mathematics, they find a much greater return of math skill in working from the latest cohort. An increase in math skills with one-standard deviation, 6.25 points provide \$ 0.24 and \$ 0.57 higher hourly wages for men who graduated in 1972 and 1980, respectively, when controlling for education, work experience, family background, race and geographical location

They find clear evidence that basic cognitive skills were a more important indicator of wages six years after completing high school in the mid-1980s than in the late 1970s. This indicates a shift in demand for workers with higher skills. They also find that the cognitive skills had much less effect on wages two years after graduating than six years after graduating, suggesting that it takes time for employers to observe skills.

Murnane Willet, Duhaldeborde and Tyler (2000) examines the relationship between adolescent cognitive skills and their wages about ten years later and find that the proportion of wage differentials in 1985 and 1991 can be explained by school grades. They use the same data sets Murnane et al. (1995), NLS72 and HS&B, to study the connection between math performance when subjects graduated high school and wages when they were 31 and 27 years old, respectively. They find that one-standard deviation increase in math skills will provide an increased annual income by 3.7% for 31-year-old men in 1985. Comparing models where they include dummy variables for highest education degree, they concluded that a third of the return of cognitive skills is an indirect effect through individuals who are more likely to finish college, if they have higher skills. They conclude that investments in school to acquire cognitive skills

will pay dividends in the workplace, but that one of the main reasons that higher skills causes higher income is due to higher likelihood to pursue higher education. This means that if a teenager should take full advantage of their skills, he or she is dependent on opportunities for higher education.

Hanushek et al. (2015) used data from PIAAC to compare returns of skills in 22 different countries. They based their study on a classic Mincer model, expanded by measure of skills. Numeracy is the explanatory variable as it easiest to compare across borders. They studied a sample of individuals in their "prime age" while working full time, since this provides the best picture of the income an individual would have during his lifetime, and thus the total return of skills. Prime age is subjects between 35 and 54 years old. They also find that better cognitive skills are largely related to higher wages. The result shows that an increase of one-standard deviation in skills mean an increase in the hourly rate of 17.8%. They find large differences between countries. Returns in the countries with the highest return (Germany, USA and Ireland) is about twice as large as in the countries with the lowest return (Norway, Sweden and the Czech Republic). They also find clearly higher returns in individuals in their "prime-age" than younger and older workers, higher return when working in private than the public sector, and higher returns by parents with higher education. The return is systematically lower in countries with strong unions and a large public sector. They test the robustness of the model by including more control variables and allow for heterogeneous effects, and concludes that in all countries in the sample is a positive correlation between skills and income.

My topic of question will lie closely to Hanushek et al. (2015) as we both use the PIAACsurvey and investigates the wage relationship. However, I concentrate on the wage differences in larger and smaller firms, and how this is effected by skills. Rather than the direct return of skills, as they do.

Summary: There has be a lot of research on firm-size premiums and return of skills. Most of them have used traditional human capital variables like years of formal education and not a direct measurement of cognitive skills. The firm-size premiums studies use either a simple measurement of employees numbers in firms, or they use firm-size dummies and compare the larger firms to the smallest firm-size category. In my examination of firm-size premiums I will use the latter. This give me the ability to compare different firm-size categories and look at different variable interaction effects with the different firm-size categories.

Chapter 4 Empirical framework and strategy

In this chapter I present the empirical strategy used to investigate the inter-dependence of wage and firm-size given worker's attributes. I will first describe the basic model used and possible problems this can give me in the estimation. The analysis by Brown and Medoff (1989) added 'standard' proxies for labor quality (such as years of schooling) to a wage function and observed a fall of about one-half in the firm-size effects. Brown and Medoff's analysis is complete only to the extent that unmeasured dimensions of labor quality, such as numeracy, are highly correlated with the observed measures so that omitted variable bias is not too severe. Hence, the current analysis can be thought of as an extension to Brown and Medoff (1989), and is made possible by the new measures of skills available from the PIAAC-survey.

4.1 General Model

Following the empirical frame-work from Gibson and Stillman (2009), I'll estimate several specifications of the following wage function:

$$lnwage_{ic} = \alpha_{c} + firmsize_{i}\theta_{c} + numscore_{i}\omega_{c} + education_{i}\pi_{c}$$
$$+ experience_{i}\varphi_{c} + experience_{i}^{2}\Xi_{c} + agecohorts_{i}\rho_{c} + X_{i}\beta_{c} \qquad (4.1)$$
$$+ jobsector_{i}\gamma_{c} + jobtype_{i}\vartheta_{c} + u_{iic}$$

lnwage_i: logarithmic hourly wage for the (*i*)th worker in the (*c*)th country,

 α_c : constant term, representing country differences.

firmsize_i: The firm-size vector consists of 4 dummy variable:

firmsize2: Firm consist of 11-50 employeesfirmsize4: Firm consist of 251-1000 employeesfirmsize3: Firm consist of 51-250 employeesfirmsize5: Firm consist of 1000+ employees

There are five firm-size dummy categories, but firmsize1, which is the category for 1-10 employees are used as a reference point and the coefficients from the other firm-size categories should be read as the relation to this category.

numscore_i: The numeracy score, standardized within-country mean of 0 and a std.dev of 1 education_i: The number of years with formal education experience_i: The number of year with job experience after finished education experience²: The experience squared and divided by 100

agecohort_i: cohort vector consisting of 4 age dummy variables:

cohort2: 39 – 42 years' old	cohort4: 47– 50 years' old
cohort3: 43 – 46 years' old	cohort5: 51 – 54 years' old

 X_i : Vector for individual's traits. Consists of dummy variables for gender and migrant status. The vector (jobtype_i) consist of 11 occupational classification of survey respondent's job The vector (jobsector_i) consist of 22 industry classification of the survey respondent's job

4.1.1 Specification error and bias

To get consistent and unbiased estimator at OLS-estimation of this equation, the error term (u_{ic}) must meet the Gauss-Markov assumptions (Verbeek, 2012 p. 15)..

- The model is linear in the parameters
- It is a random and representative sample
- The expected value of the error term is zero for all observations

$$E\{u_{ic}\} = 0, \qquad i, c = 1, ..., N$$

- Homoscedasity: the error term (u_i) has the same variance given the values of all explanatory variables.

$$V(u_i) = E(u_i^2) = \sigma_u^2,$$
 i, *c* = 1, ..., *N*

- No autocorrelation. The error term is independently distributed and not correlated. No perfect collinearity and no perfect linear correlation between any of the variables

$$cov\{u_i, u_j\} = 0$$
 $i, j = 1, ..., N$, $i \neq j$.

- Error terms and explanatory variables are not correlated

$$\{u_1, \dots, u_N\}$$
 and $\{x_1, \dots, x_N\}$ are independet

If all the Gauss-Markov assumptions are met, then the OLS estimator are BLUE: best linear unbiased estimators.

Since there are so many factors that determine an individual's income, one of the main estimation problem is to find causal effect of firm-size. It is possible to have an omitted variable bias

Chapter 4 Empirical framework and strategy

4.1.2 Omitted variable bias

If one is (implicitly) assuming that the conditioning set of the model contains more variables than the ones that are included, it is possible that the set of explanatory variables is "misspecified" This means that one or more of the omitted variables are relevant, i.e. have nonzero coefficients. To illustrate this, consider the following two models

$$y_i = \beta_0 + \beta_1 firmsize_i + u_i \tag{4.2}$$

and

$$y_i = \beta_0 + \beta_1 firmsize_i + \beta_2 X_i + v_i \tag{4.3}$$

both interpreted as describing the conditional expectation of (y_i) given $(firmsize_i)$ and X_i . Where $firmsize_i$ is the firm-size category dummy the individual is located in. The model in (4.2) is nested in (4.3) and implicitly assumes that X_i is irrelevant ($\beta_2 = 0$). So a problem arises when estimating equation (4.2) when in fact equation (4.3) is the correct one. If it is the case that the X_i variable influences the dependent variable, but if not include into the equation, it will appear in the residual. In such a way:

$$u_i = \beta_2 X_i + v_i \tag{4.3}$$

The probability boundary of the estimator will then be given by:

$$plim(\widehat{\beta_1}) = \beta_1 + \frac{\beta_2 cov(firmsize_i, X_i)}{var(firmsize_i)}$$
(4.4)

If $cov(firmsize_i, X_i) = 0$, the estimator would still be consistent. However, if there is a correlation between the explanatory variable and the unobservable/omitted variable such that $cov(X_i, u_i) \neq 0$, there is a violation of preconditions, assumption for consistency of OLS. Resulting in a biased estimator. The direction of this bias depends on the direction of correlation. This will cause problems in the model (4.2) if there are variables not included in the equation, but is correlated with firm-sizes. There could be a variable causing "self-selection", where there is an unobservable variable that is making workers sort into different firm-sizes.

4.1.3 Measurement error in the explanatory variable

A situation where the OLS estimator is likely to be inconsistent arises when an explanatory variable is subject to measurement error. In my case, when using firm-size dummies as explanatory variables. This is potentially a problem since we do not observe the actual firm-size, but what the individual survey responder reports, which could be wrongly reported. If the conducted survey observation does not give accurate observation, the OLS-estimators will be biased. Measurement error may also occur if the firm-size does not capture all variation in the differences between small and large firms, as it may also depend on unobservable variety. To illustrate this, look at the simplified equation:

$$y_i = \beta_0 + \beta_1 firmsize_i + u_i \tag{4.5}$$

If there exists a measurement error the $firmsize_i$ variable is given by:

$$firmsize_i^* = firmsize_i + \mu_i \tag{4.6}$$

The variable used in the estimations is thus not the true value of the firm-size variable. The measurement error, given by (μ_i) , will lead to a bias in the estimate of equation (4.5) Measurement error in explanatory variable makes the estimator biased toward zero. (Wooldridge, 2009, p. 319) The potential measurement error gives reason to perceive OLS estimate as a lower limit for return of larger firm-sizes.

4.1.4 Heteroscedasticity

Heteroscedasticity refers to the circumstance in which the variability of a variable is unequal across the range of values of a second variable that predicts it. To account for a possible heteroscedasticity, I will use robust standard deviation estimations. A violation of the assumption of homoscedastic will not lead to unequal estimators, but will give errors in the t-and F distributions and thereby create problems for test utilizing these. (Wooldridge, 2009, p. 265) Heteroscedasticity:

$$E\{u_{ic}\} = \sigma^2 \begin{bmatrix} \sigma_1^2/\sigma & \cdots & 0\\ \vdots & \ddots & \vdots\\ 0 & \cdots & \sigma_n^2/\sigma^2 \end{bmatrix} = \sigma^2 \Omega$$

$$(4.7)$$

Notice, under homoscedasticity, $\Omega = I$. Under heteroscedasticity, the sample variance of OLS estimator (under finite sample properties) is:

$$V(\hat{\beta}) = \sigma^2 (X'X)^{-1} X \Omega X (X'X)^{-1}$$

$$\tag{4.8}$$

One common way to solve this problem is to estimate (Ω) empirically: First, estimate an OLS model, second, obtain residuals, and third, estimate (Ω)

$$\widehat{\Omega} = \begin{bmatrix} \widehat{u}_i^2 & \cdots & 0\\ \vdots & \ddots & \vdots\\ 0 & \cdots & \widehat{u}_n^2 \end{bmatrix}$$
(4.9)

Therefore, we can estimate the variances of OLS estimators (and standard errors) by inserting $(\widehat{\Omega})$ into equation (4.8)

$$V(\hat{\beta}) = \sigma^2 (X'X)^{-1} X \widehat{\Omega} X (X'X)^{-1}$$
(4.10)

4.1.5 Cross-sectional data

When estimating the pooled sample by combining every country we could experience some estimation errors. The data given in the PIAAC-survey is hourly wage in the countries own currencies. I need a method for looking at within effects of each country when estimating the pooled sample. Fixed effects estimation could give more accurate results, which only uses variation within group (here countries) to determine coefficients. Since this is only cross-sectional data (one time-period) it does not diminish the possibility of omitted variable problem as much as if it was panel data with several observations over time. Given this, I will use fixed effects for the pooled specification and give the same weight to each country, so the all estimates rely just on within-country variation. This is the same strategy used in Hanushek et al (2015)

Cohort effects

I have in the base model, equation (4.1), including dummy variables for cohorts to catch up any differences in returns associated with differences in age groups which may be due to variations in the number of births in the period, economic conditions and so on. It will be necessary to control for cohort effects if there have been fluctuations in labor supply that has been able to influence wage structure in the labor market.

Summary: In this chapter I have presented the empirical framework and strategy used for examining my topic of question. I have also looked at problems with specification error, possible biases heteroscedasticity when estimating my model. I have also presented why I will use fixed effects to capture the within-variation when estimating the pooled sample.

Chapter 5 Data description

I will in this chapter describe the data for my empirical work. I will first describe the PIAACsurvey, which collected the data used in this thesis, how the data was collected and how direct cognitive skills were measured. Later in the chapter I will describe the variables used in my estimation. Last I illustrate the firm-size premiums observed in the PIAAC-data

5.1 PIAAC

The data used in this thesis derives from the PIAAC-survey (Programme for the International Assessment of Adult Competencies) from 2013 conducted by OECD⁶

The survey will measure the adult individual's cognitive skills that are requisite to function in society. The survey results should help countries to better understand how education and job training can improve these skills. Educators, governments and economists can use the information to develop policies and guidelines to improve adult skills (Bjørkeng, 2013).

The survey was developed by OECD and implemented in 24 countries. 21 of which can be used in my analysis: Austria, Belgium, Canada, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, Russia, the Slovak Republic, Spain, Sweden, the United Kingdom and the United States. In each participating country, a representative sample of adults between the age of 16-65 were interviewed in their homes and solved tasks on computers, or on paper if they lacked computer knowledge. The survey was conducted in two phases; a main phase in December 2011 and a follow-up phase in April 2013. The questions test individuals' literacy skills, numeracy and problem solving in technology-rich environments, in addition to background information on the participants and how these skills are used in work and everyday life. The survey is designed so that the results are comparable across national boundaries and the goal is to repeat the survey later so that you can monitor their progress over time.

Similar studies had been carried out on literacy and numeracy earlier: IALS (the International Adult Literacy Survey) from 1998 and ALL (The Adult Literacy and Life Skills Survey) of 2003.

⁶ Organisation for Economic Cooperation and Development. http://www.oecd.org/site/piaac/

Cognitive skills tests

The survey included an assessment of cognitive skills in three domains: literacy, numeracy, and problem solving in technology-rich environments. The tasks respondents had to solve were often framed as real-world problems, such as maintaining a driver's logbook (numeracy domain) or reserving a meeting room on a particular date using a reservation system (problem-solving domain). The domains, described more completely in OECD (2013), refer to key information- processing competencies and are defined (Hanushek, et al. 2015).

- 1. Literacy: Ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential.
- 2. Numeracy: Ability to access, use, interpret, and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life;
- 3. Problem solving in technology-rich environments: Ability to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks.

PIAAC measures each of the three skill domains on a 500-point scale. For analytical purposes, as Hanushek, et al. (2015), I use the standardize scores in the subsequent regression analyses to have a within-country mean of zero and a within-country standard deviation of one. All three scales are intended to measure different dimensions of a respondent's skill set. IALS, the predecessor of PIAAC, suffered from pairwise correlations of individual skill domains that exceeded, making it virtually impossible to distinguish between different skills (Hanushek, et al. 2015). If the participant is good at reading, it's likely that he also has good numeracy understanding. When all the skills included in the model, there will be collinearity between variables that complicate finding the separate effects of the individual skill on income. Hanushek et al. (2015) addresses this by using only numeracy as an explanatory variable and also argue that this is more easily compare across national borders than reading skills. I will also only use numeracy scores as a proxy for cognitive skill. When the numeracy score are standardized to within-country mean of zero and a within-country standard deviation of one, and we have a logarithmic left side variable. Multiplying the coefficients with 100, can be read as the percentage wage growth of one-standard deviation change in the variable.

Before the skill assessment, all participants responded to a background questionnaire that gathered information about labor-market status, earnings, education, experience, and demographic characteristics of the respondents. The measure of experience refers to actual work experience and was collected as the number of years where at least 6 months were spent in paid work. The PIAAC-data set used in this thesis is identical to the data used in Hanushek et al (2013), added a firm-size variable by my advisor, Bjarne Strøm.

5.1.1 Sampling Weights

Sampling weights are designed to make the data representative of the target population by compensating for the disproportionate sampling of subgroups and non-coverage. Reducing sampling errors by making use of known data for the population, minimizing possible biases arising from differences between respondents and non-respondents, and facilitating the estimation of variances through the use of the replication. PIAAC has its own requirements for this weighting and calibration (Gravem and Lagerstrøm, 2013) I have included the PIAAC sampling weights in my estimations.

5.1.2 Data adjustments

The data is trimmed by removing the top and bottom 1% of income observations. This is done to get a more balanced view and remove possible wrong data inputs. As mention in chapter (4), I will also specify the estimation sample to full time working individuals in their "prime age". This is defined being the age between 35 and 54, as this is the age where we get the clearest picture of the life cycle income. Individuals than this younger will most likely be in the start of their career and will probably increase their wage in the years to come. The most skilled of them will increase their wage faster than average and therefor the wage early in someone's career will give a skewed picture when analyzing firm-size premiums.

5.2 Variables

Here I describe the variables used in my estimations.

5.2.1 Dependent variable

The dependent variable used in the econometric models are logarithmic value of income in terms of gross hourly wages without bonuses. The data comes from a Public Use File. In each country, we trim the bottom and top one percent of the wage distribution to limit the influence of outliers. Examining the hourly rate to form a clearer picture of the different firm-sizes, because it excludes out the effect that the increased income also depends on the number of hours each week. The logarithmic function gives a good picture of the relationship between education and income, and in addition, results are easy to interpret.

5.2.2 Explanatory variables

The important explanatory variables in this paper is the dummy variables for different firmsizes. The firm-sizes were gathered from the different PIAAC survey participants and split into five different dummy categories. The dummies equals 1 when the individual participants is located in the specific firm-size category, 0 if not. The dummy variables are: 1 to 10 employees, 11 to 50 employees, 51 to 250 employees, 251 to 1000 employees and more than 1000 employees. Making:

 $firmsize1_i, firmsize2_i, firmsize3_i, firmsize4_i$ and $firmsize5_i$

5.2.3 Control variables

I base the control variables in the Mincer-model (Mincer, 1974), while adding numeracy and migrant-status of the individual. This give the following control variables:

Direct cognitive skill and skill proxy measurements.

 $numscore_i$: The numeracy test score,education_i: The number of years withstandardized within-country mean of 0 withcompleted formal education.a stand.dev of 1

Other control variables

When trying to differentiate the effect of the direct cognitive skill and proxy variables on firmsize premiums, it is important to control for other variables that may influence the estimation. These variables are included to get a clearer picture of the changes in the different specifications of the model

experience_i: The number of year with job experience after finished education

 $experience_i^2$: The experience squared and divided by 100 to more clearly show the effect.

 $female_i$ – Dummy variable equal to 1 if the individual is a woman.

 $first_migrant_i$ - Dummy variable equal to 1 if the individual is a migrant.

jobtype_i- dummy variable consist 11 occupational classification of survey respondent's job

jobsector_i- dummy variable consist of 22 industry classification of the survey respondent's job

Jobtype and jobsector are used as controls to mitigate the effects of higher-paying occupations and industry sectors. The different job types and job sector dummies are described in appendix, tables (A1 and A2)

5.3 Descriptive statistics

Table 2 Number of observations in firm-size categories. Data source: PIAAC

	Pooled	Austria	Belgium	Canada	Czeck.	Denmark	Estonia	Finland	France	Germany	Ireland
1 - 10	10388	281	256	2086	477	505	821	510	505	291	300
11 - 50	14458	423	394	2938	490	1033	1092	713	628	471	409
51 - 250	11856	344	468	2355	382	904	641	511	573	464	303
251 - 1000	6132	209	246	1254	159	341	221	241	342	310	224
1000+	4207	139	159	836	66	274	86	111	226	223	119
Total	47041	1396	1523	9469	1574	3057	2861	2086	2274	1759	1355
	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.	U.S.
1 - 10	415	415	438	661	216	346	290	147	370	506	343
11 - 50	375	375	582	505	414	631	363	278	542	494	600
51 - 250	291	291	496	361	426	524	306	244	443	328	475
251 - 1000	127	127	237	177	223	245	128	90	223	170	252
1000+	136	136	163	134	153	261	89	69	91	94	187
Total	1344	1344	1916	1838	1432	2007	1176	828	1669	1592	1857

Means, standard deviations (in parentheses), and numbers of observations for selected variables by country. Sample: full-time employees aged 35–54. Full-time workers are defined as those working at least 30 h per week

Chapter 5 Data description

Table 2 describes the sample used in this paper. Data from 21 countries are available for this analysis. There is a total of 47041 firm-size observations. There is a good deal of variation across the sample, emphasizing the potential value of studying the firm-size premiums for several countries. The firm-size distribution is mostly skewed towards smaller firms.

	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
1 to 10	263.7	275.8	276.4	254.1	272.7	276.1	269.7	278.5	249.6	269.3	258.1
	(50.64)	(48.95)	(46.19)	(54.08)	(42.45)	(47.71)	(43.53)	(48.46)	(52.21)	(47.03)	(50.37)
11 to 50	272.4	284.1	283.4	262.0	275.7	282.0	272.1	287.8	260.1	276.1	268.6
	(49.26)	(46.70)	(49.24)	(52.32)	(41.20)	(47.09)	(41.99)	(46.40)	(53.88)	(49.49)	(47.44)
51 to 250	278.4	285.9	286.9	268.8	284.4	289.9	277.0	295.0	263.8	281.2	270.3
	(49.32)	(46.89)	(47.48)	(52.34)	(46.46)	(46.00)	(44.25)	(45.94)	(53.50)	(49.77)	(51.36)
251 to 1000	283.2	291.0	293.3	275.5	283.5	293.2	277.0	303.0	268.7	292.2	284.1
	(49.93)	(48.59)	(51.93)	(51.08)	(41.33)	(51.69)	(44.47)	(45.16)	(53.13)	(49.25)	(44.18)
1000+	290.3	293.3	305.7	283.4	278.9	307.3	274.6	298.5	278.8	301.8	291.7
	(49.35)	(46.06)	(51.37)	(50.19)	(40.30)	(43.57)	(48.95)	(45.66)	(52.22)	(42.20)	(52.21)
Average	275.0	284.8	287.2	265.6	277.8	286.9	272.9	289.6	261.8	282.4	271.2
	(50.31)	(47.68)	(49.48)	(53.09)	(43.10)	(47.84)	(43.42)	(47.25)	(53.75)	(49.27)	(49.91)
	Italy	Japan	Korea	Nether	l. Norwa	y Polanc	l Slovak	. Spain	Sweden	U.K.	U.S.
1 to 10	243.7	283.5	250.1	273.3	285.4	253.4	281.6	244.0	276.1	264.9	250.9
	(50.22) (44.34) (45.11) (45.56)	(46.70)	(48.86)) (37.59)	(53.28)	(52.62)	(52.62)	(55.99)
11 to 50	264.9	290.3	258.1	286.2	287.4	262.4	281.1	252.7	286.0	265.2	261.6
	(46.54) (42.59) (46.45) (50.29)	(47.25)	(48.18)) (42.68)	(48.55)	(46.26)	(50.16)	(52.53)
51 to 250	263.2	296.7	266.7	295.0	295.1	265.0	282.0	262.5	291.3	276.2	261.4
	(45.44) (42.74) (43.49) (41.75)	(47.94)	(46.90)) (40.51)	(45.84)	(45.94)	(50.45)	(54.36)
251 to 1000	271.6	303.3	272.3	296.2	302.0	265.9	288.3	270.8	298.7	274.6	266.5
	(47.03) (41.13) (39.96) (49.72)	(46.17)	(46.11) (38.67)	(45.72)	(49.17)	(51.74)	(56.79)
1000+	263.0	· · ·		295.2	306.7	271.0		263.6	300.9	282.7	279.7
	(47.73) (40.79) (40.65) (46.83)	(43.70)	(45.73)) (38.43)	(46.66)	(53.00)	(48.20)	(52.41)
Average	258.4	295.1	260.5	289.4	293.4	261.9	283.1	254.5	288.8	272.1	263.2
	(48.63) (44.20) (45.68) (47.31)	(47.31)	(47.83) (40.36)	(49.95)	(49.09)	(50.98)	(54.86)

Table 3 Average numeracy scores for the workers in the different firm-size categories. Data source: PIAAC

Notes: Means, standard deviations (in parentheses), and numbers of observations for selected variables by country. Sample: full-time employees aged 35–54. Full-time workers are defined as those working at least 30 h per week

In table (3) I observe a sorting of workers with higher numeracy scores into larger firms. The pooled results show an increasing average numeracy score in the different firm-size categories. With 10% higher average numeracy scores for respondents working in 1000+ employee firms. Respondents in Japan achieve the highest average numeracy score, and respondents in Italy the lowest, with a difference in average achievement between these two countries amounting to 89% of a standard deviation in test scores in the international sample This emphasize the potential value of studying the hypothesis that firm-size premiums are caused by higher skilled employees in larger firms. Further, I will examine if numeracy influence the wage effect of different firm sizes. I also find that workers in large firms has a higher education level compared

to small workers in small firms. In the Pooled sample, 1000+ employee' firms have on average 1.8 more years of education than workers in 1-10 employee firms. Please see table (A3) in the appendix for average number of year of education for each country and sorted into firm-size categories. The average years of formal education is 13.44 years. Subjects form Ireland has the highest average of 15.84 years and France has the lowest of 11.82 years.

Next I show a figure depicting descriptive statistics for the gross hourly wage in countries own currency, wage inequality, measured by the log wage differential between the 90th and 10th percentile of the wage distribution, experience, female share and migrant share.

Table 4 Descriptive statistics. Data source: Hanushek, et al. (2015), with modifications.

	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
Gross hourly wage		15.3	18.0	27.4	117.0	198.5	5.2	18.6	13.7	17.2	21.3
(national currency)		(6.1)	(6.1)	(11.9)	(50.8)	(62.4)	(3.3)	(6.7)	(5.6)	(7.8)	(10.3)
Wage inequality	1.11	1.07	.85	1.25	.96	.78	1.51	.88	.86	1.35	1.20
	(49.8)	(49.2)	(49.6)	(53.5)	(43.1)	(45.3)	(44.0)	(47.6)	(53.0)	(49.5)	(49.9)
	(2.9)	(2.6)	(2.6)	(2.5)	(2.4)	(2.5)	(2.6)	(2.8)	(3.4)	(2.5)	(2.8)
Experience (years)	22.3	24.9	23.2	23.5	22.4	24.4	22.0	21.0	22.5	23.3	22.0
	(7.8)	(7.4)	(7.0)	(8.0)	(7.4)	(7.8)	(7.2)	(7.4)	(8.0)	(7.5)	(7.7)
Female (share)	.43	.34	.39	.49	.50	.49	.56	.51	.44	.39	.41
Migrant (share)	.13	.13	.07	.18	.19	.11	.03	.03	.10	.12	.16
Observations	42,912	1,115	1,220	7,178	1,066	1,875	1,767	1,478	1,715	1,296	1,031
	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.	U.SA
Gross hourly wage	Italy 11.7	Japan 1.9 ^a	Korea	Netherl.	Norway 235.8	Poland 16.4	Slovak R.	Spain 10.4	Sweden 172.2	U.K. 14.3	U.SA 24.3
Gross hourly wage (national currency)	2	-			2						
, ,	11.7	1.9 ^a	13.0 ^a	19.7	235.8	16.4	4.4	10.4	172.2	14.3	24.3
(national currency)	11.7 (5.5)	1.9 ^a (1.1)	13.0 ^a (8.7)	19.7 (7.7)	235.8 (75.2)	16.4 (9.2)	4.4 (2.7)	10.4 (5.2)	172.2 (49.4)	14.3 (7.6)	24.3 (15.0)
(national currency)	11.7 (5.5) 1.02	1.9 ^a (1.1) 1.31	13.0 ^a (8.7) 1.50	19.7 (7.7) 1.06	235.8 (75.2) .80	16.4 (9.2) 1.25	4.4 (2.7) 1.22	10.4 (5.2) 1.21	172.2 (49.4) .69	14.3 (7.6) 1.20	24.3 (15.0) 1.49
(national currency)	11.7 (5.5) 1.02 (47.7)	1.9 ^a (1.1) 1.31 (42.1)	13.0 ^a (8.7) 1.50 (43.5)	19.7 (7.7) 1.06 (47.0)	235.8 (75.2) .80 (48.9)	16.4 (9.2) 1.25 (46.8)	4.4 (2.7) 1.22 (40.3)	10.4 (5.2) 1.21 (46.7)	172.2 (49.4) .69 (50.6)	14.3 (7.6) 1.20 (51.9)	24.3 (15.0) 1.49 (54.7)
(national currency) Wage inequality	11.7 (5.5) 1.02 (47.7) (3.6)	1.9 ^a (1.1) 1.31 (42.1) (2.4)	13.0 ^a (8.7) 1.50 (43.5) (3.0)	19.7 (7.7) 1.06 (47.0) (2.5)	235.8 (75.2) .80 (48.9) (2.3)	16.4 (9.2) 1.25 (46.8) (2.9)	4.4 (2.7) 1.22 (40.3) (2.5)	10.4 (5.2) 1.21 (46.7) (3.5)	172.2 (49.4) .69 (50.6) (2.4)	14.3 (7.6) 1.20 (51.9) (2.3)	24.3 (15.0) 1.49 (54.7) (2.9)
(national currency) Wage inequality	11.7 (5.5) 1.02 (47.7) (3.6) 20.8	1.9 ^a (1.1) 1.31 (42.1) (2.4) 21.3	13.0 ^a (8.7) 1.50 (43.5) (3.0) 16.2	19.7 (7.7) 1.06 (47.0) (2.5) 22.9	235.8 (75.2) .80 (48.9) (2.3) 22.2	16.4 (9.2) 1.25 (46.8) (2.9) 20.7	4.4 (2.7) 1.22 (40.3) (2.5) 22.4	10.4 (5.2) 1.21 (46.7) (3.5) 20.5	172.2 (49.4) .69 (50.6) (2.4) 22.4	14.3 (7.6) 1.20 (51.9) (2.3) 24.5	24.3 (15.0) 1.49 (54.7) (2.9) 24.0
(national currency) Wage inequality Experience (years)	11.7 (5.5) 1.02 (47.7) (3.6) 20.8 (8.4)	1.9 ^a (1.1) 1.31 (42.1) (2.4) 21.3 (7.0)	13.0 ^a (8.7) 1.50 (43.5) (3.0) 16.2 (7.9)	19.7 (7.7) 1.06 (47.0) (2.5) 22.9 (7.3)	235.8 (75.2) .80 (48.9) (2.3) 22.2 (7.4)	16.4 (9.2) 1.25 (46.8) (2.9) 20.7 (7.7)	4.4 (2.7) 1.22 (40.3) (2.5) 22.4 (7.0)	10.4 (5.2) 1.21 (46.7) (3.5) 20.5 (8.0)	172.2 (49.4) .69 (50.6) (2.4) 22.4 (7.7)	14.3 (7.6) 1.20 (51.9) (2.3) 24.5 (7.4)	24.3 (15.0) 1.49 (54.7) (2.9) 24.0 (8.1)

Notes: Means, standard deviations (in parentheses), and numbers of observations for selected variables by country. Sample: full-time employees aged 35–54. Full-time workers are defined as those working at least 30 h per week. Wage inequality: log wage differential between 90th and 10th percentile of wage distribution. Pooled specification gives same weight to each country

In table (4), I observe considerable variation across countries in average actual work experience, and the share of females and migrants in the population of prime-aged, full-time employees. Wage inequality, measured by the log wage differential between the 90th and 10th percentile of the wage distribution, is largest in Estonia, Korea, and the United States at around 1.5. In these countries, a worker at the 90th percentile of the wage distribution earns 4.5 times as much as a worker at the 10th percentile. In Sweden, which is the other extreme, workers at the 90th percentile earn only twice as much as workers at the 10th percentile (Hanushek et al. 2015). This may influence the effect of firm-sizes on wages. Countries with small wage differences will most likely have smaller firm-size premiums.

5.4 Raw data firm-size premiums

Here I present a figure, illustrating the firm-size premiums I find using the PIAAC-data. This is done by estimating the logarithmic hourly wage using firm-size dummies as explanatory variables. I examine the "raw" data.

$$lnwage_{ijc} = \alpha_c + firmsize_j\theta_c + u_{ijc}$$
(5.1)

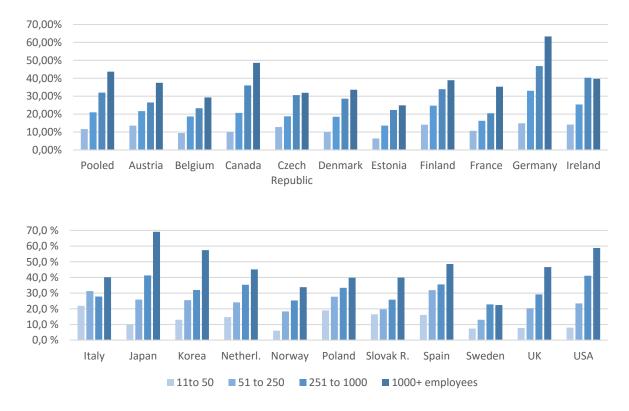


Figure 1. Percentage wage gain over the base firm-size category (1-10 employees). Raw data

Results from least squares regressions. Dependent variable: log hourly wage. Sample: full data set. Pooled specification includes country fixed effects and gives same weight to each country. Full table (A4) in appendix,

Figure (1) illustrates the percentage wage gain workers have, on average, in the four firms-size categories compared to workers in firm consisting of 1-10 employees. From figure (1), we can see that "raw" firm-size premiums exist in all 21 countries and that they vary greatly for each individual country.

The pooled estimation shows that workers in larger firms, on average, earn 11.7% to 43% more than workers in firms with 10 or less employees. In the raw data we can clearly observe firmsize premium across the whole sample.

Nordic countries (Norway, Sweden, Denmark and Finland)

Examining the Nordic countries if find that every country has firm-size premiums, however they are smaller than the pooled estimation. Finland has the largest premiums with workers in larger firms on average, earn 14% to 39% more than workers in firms with 10 or less employees. In Norway the firm-size premiums vary from 6% to 33%, in Denmark from 10% to 33.6%. The smallest firm-size premiums are found in Sweden, where they vary from 7.4% to 22.4%

English speaking countries (United States, United Kingdom, Canada and Ireland)

In the English speaking countries, I find that the firm-size premiums vary from 14.2% to 39.7% for Ireland, 7.7% to 46.6% for the United Kingdom, 10.1% to 48% in Canada and 7.9% to 58.8% for the United States. Comparing the UK and USA with Norway, Denmark and Sweden, I find that the firm-size premiums for workers in the 11-50 employee firms are very similar, but when comparing the largest firm-size category, I find large differences between the countries. There is a firm-size premiums rise much more in the UK and especially in the USA.

Continental west Europe (Germany, France, Italy, Spain, Austria, Belgium)

Examining the west European countries, I find firm-size premiums to be; 14,9% to 63.3% in Germany, 10.7% to 35.5% in France, 21.9% to 40.1% in Italy, 16.1% to 48.6% in Spain, 13.6% to 37.5% in Austria and 9.4% to 29.3% in Belgium.

Former communist countries (Czech Republic, Estonia, Poland, Slovak Republic)

Looking that the former communist countries, I find that the firm-size premiums range from 12.8% to 31.9% in the Czech Republic, 6.4% to 24.9% in Estonia, 19% to 38.8% in Poland and 16.5% to 39.9% in the Slovak Republic.

Asian countries (Japan, Korea)

Examining the two Asian countries at my disposal I find that both Japan and Korea has large firm-size premiums compared with the pooled sample. The premiums range from 9.8% to 69.1% in Japan and 13% to 57.4% for Korea. Along with Germany and the United states, are these are the largest firm-size premiums in the whole sample.

The return of firm-size seems to be linear for every country except, Italy, Sweden and Ireland. These are the only countries without a continuous rise in worker's hourly earnings when going

Chapter 5 Data description

up firm-sizes. Looking at Italy it is shown that the workers in the firm-size category 51 to 250 employees earn 31.3 percent more than smallest firm-size, while the category for firm with 251 to 1000 employees earns 27.8 percent more than employees in the smallest firm-size. In Sweden and Ireland, the wage actually decreases by 4 and 6 percent, respectively, when going from the second largest to the largest firm-size category. The other countries have similar but different sizes of the firm-size premiums. Several of the countries have significant jump in the 11 to 50 and in the 1000+ employee category.

There seems to be a trend in the data, where the more capitalistic countries like USA, Germany, Korea and Japan has the largest firm-size premiums, and the Nordic countries together with some of the former communist countries have a less differences in firm-size premiums. There are many possible reasons for the country differences in firm-size premiums, but different forms of economic systems may answer some of these differences. The countries with the largest firm-size premiums also have the largest wage spreads in the sample. As stated above the wage spread will most likely influence the firm-size effects on wages.

Summary: In this chapter I have presented the dependent, explanatory and control variables used in my empirical estimations. I have presented descriptive statistics and shown the potential to test how labor quality effects the firm-size premium. Last I have illustrated the "raw" firm-size premiums, which I find in every country.

Chapter 6 Empirical results

In this chapter I will present my empirical results. I will base my results of estimation with different specifications of model (2.18) I will start by using the model above for the raw data and adding control variables for "prime-age" groups, character characteristics, job sector and job type of the individual. To obtain a homogenous sample of workers with strong-labor commitments, I limited the estimation sample to survey respondents who work-full time at the time of the survey, and are of the age 35-54. Full-time employees are defined as those working at least 30 hours per week. I will examine if the firm-size premiums diminished or dissolves when taking into account different control variables. I will use the f-statistics to test the following hypothesis:

 $H_0: \theta_c = 0 \iff H_0: \theta_2 = \theta_3 = \theta_4 = \theta_5 = 0$ $H_A: \theta_c \neq 0$

The zero hypothesis is that the firm-size coefficients are statistically equal to zero. Meaning that the firm-size categories have no significant impact on the hourly wage of the individual. The alternative hypothesis is that firm-size dummies are not equal to zero.

6.1 Model 1 Base Control variables

 $lnwage_{ic} = \alpha_c + firmsize_i\theta_c + agecohorts_i\rho_c + X_i\beta_c + jobsector_i\gamma_c$ (6.1) + jobtype_i\vartheta_c + u_{ic}

Table 5 Effect of firm-size on wages. Base control variables

	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
11to 50	0.079***	0.099***	0.019	0.094***	0.090**	0.077***	0.068**	0.079***	0.060**	0.060	0.184***
	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)
51to 250	0.129***	0.141***	0.065**	0.155***	0.123***	0.094***	0.112***	0.145***	0.101***	0.185***	0.245***
	(0.01)	(0.03)	(0.02)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.05)
251to1000	0.200****	0.163***	0.124***	0.244***	0.184***	0.168***	0.193***	0.181***	0.129***	0.248***	0.337***
	(0.01)	(0.03)	(0.03)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)	(0.05)
1000+	0.263***	0.170***	0.129***	0.284***	0.183**	0.190***	0.117^{*}	0.205***	0.233***	0.367***	0.270***
	(0.02)	(0.03)	(0.03)	(0.02)	(0.06)	(0.02)	(0.06)	(0.03)	(0.03)	(0.04)	(0.06)
N	42912	1255	1374	9136	1348	2933	2356	2003	2090	1626	1215
R^2	0.368	0.508	0.362	0.470	0.435	0.407	0.442	0.560	0.457	0.481	0.367
F-stat.	140.791	9.950	9.088	54.791	6.534	28.940	8.518	30.623	22.072	30.629	12.052

Table 5	continued

	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak.	Spain	Sweden	U.K.	USA
11to 50	0.094**	0.070*	0.090**	0.087**	0.058**	0.161***	0.091**	0.030	0.035*	0.143***	0.077
	(0.03)	(0.032)	(0.032)	(0.026)	(0.021)	(0.035)	(0.033)	(0.029)	(0.014)	(0.035)	(0.041)
51to 250	0.150***	0.137***	0.169***	0.166***	0.125***	0.173***	0.108**	0.149***	0.068***	0.165***	0.160***
	(0.04)	(0.033)	(0.036)	(0.026)	(0.022)	(0.035)	(0.034)	(0.032)	(0.015)	(0.036)	(0.042)
251to1000	0.183***	0.245***	0.245***	0.199***	0.131***	0.225***	0.151***	0.190***	0.130***	0.238***	0.266***
	(0.05)	(0.041)	(0.048)	(0.029)	(0.026)	(0.049)	(0.042)	(0.040)	(0.020)	(0.038)	(0.047)
1000+	0.258***	0.406***	0.476***	0.225***	0.178***	0.322***	0.242***	0.280***	0.127***	0.309***	0.322***
	(0.05)	(0.043)	(0.054)	(0.037)	(0.027)	(0.055)	(0.052)	(0.043)	(0.020)	(0.039)	(0.051)
N	1169	1751	1720	1328	1580	1018	1513	1396	1799	2106	1507
R^2	0.412	0.470	0.533	0.448	0.442	0.474	0.376	0.485	0.492	0.479	0.465
F-stat.	17.218	16.111	9.911	6.282	16.938	9.911	6.282	16.938	16.015	18.328	15.486

Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Sample: full-time employees aged 35–54. Numeracy score standardized to std. dev. 1 within each country. Experiencesq divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2 . Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001 Full table (A5) is presented in the appendix

Table (5) displays the coefficients on the dummy variables for the four firm-size categories (11–50, 51–250, 251-1000 and 1000+ employees). When adding the control variables specified above, we can observe that firm-size premiums are reduced in every country, but it is still prevalent. With a F-test and a critical value at a 1% significance-level ($F_{crit} = 2.576$) H_o can be dismissed if $F_{obs} > F_{crit}$. The f-statistics in every country is larger than the critical value. Meaning I can dismiss the zero hypothesis by a large margin.

Next I comment on the percentage point reduction in this estimation compared to the results of the "raw" specification (5.1).

Pooled (all countries)

The firm-size coefficients on the pooled regressions is reduced by; 3.8 percentage points for the 11-50 employee category, 8.1 percentage points for the 51 - 250 employee category, 12 percentage points for the 251 - 1000 employee category and 17.4 percentage points for the 1000+ categories.

Nordic countries (Norway, Sweden, Denmark and Finland)

The firm-size premiums are reduced by between; 0.24 - 16 percentage points for Norway, 2.3 - 14.6 percentage points in Denmark, 3.9 - 9.7 percentage points in Sweden and 6.2 - 18.4 percentage points in Finland.

English speaking countries (United States, United Kingdom, Canada and Ireland)

The firm-size premiums are reduced by between; (-4.2) - 12.7 percentage points in Ireland (-6.54) - 15.7 percentage points in the United Kingdom, 0.7 - 20.2 percentage points in Canada and 0.27 - 26.6 percentage points in the United States. In Ireland the largest firm-size premiums have all been reduced but interestingly the premiums for workers working in firms with 11-50 employees has, on average, actually increased.

Continental west Europe (Germany, France, Italy, Spain, Austria, Belgium and Netherlands) In the continental west Europe, the firm-size premiums are reduced by; 3.7 - 20.5 percentage points in Austria, 7.55 - 16.4 percentage points in Belgium, 4.7 - 12.0 percentage points in France, 6 - 22.6 percentage points in Netherlands, 13.1 - 20.6 in Spain, 8.9 - 26.6 percentage points in Germany and 9.5 - 16.3 percentage points in Italy.

Former communist countries (Czech Republic, Estonia, Poland, Slovak Republic)

Looking at the former communist countries we can observe a drop of; 3.8 - 13.6 percentage points in the Czech Republic, (-0.04) - 13.2 percentage points in Estonia, 2.9 - 10.6 percentage points for Poland and 7.4 - 15.7 in Slovak Republic.

Asian countries (Japan, Korea)

In the Asian countries the firm-size premiums fall by: 2.8 - 28.5 percentage points for Japan and 4 - 9.8 percentage points for Korea.

The largest drops are found in Germany, United states and Japan. However, this is somewhat expected since these were also the countries with the largest firm-size premium. Japan has the largest firm-size premium with a gain of 40.6% for workers in the 1000+ employee firm category, over the base category of 1-10 employees. The continues rise in average hourly wage is still prevalent in the countries where it was in the raw data and the same in composition in Italy, Sweden and Ireland where they did not raise continuously.

Effect of other control variables

Please see full table (A5) in appendix. On average, the experience terms suggest a concave earnings–experience relationship, since the quadratic experience coefficient is negative, meaning the second derivative of experience is negative. The experience coefficient for the pooled sample is 0.017, meaning if all else equal, one additional year of experience increases the hourly wage by 1.7%. Experience has the largest effect on hourly wages in Japan where one additional year of experience increases the hourly wage by 3.3% and the smallest in Norway and Sweden with 0.9%.

Cohort effects should be interpreted with curtesy to the base cohort (*cohort*1). The age cohorts used here shows different effect over base cohort (aged 35-38) up to the last cohort in the "prime age" interval (51-54). The pooled estimation shows an hourly wage increase of 3.2% for *cohort*5 over *cohort*1. The largest cohort effect is shown in Belgium where seniority in the "prime age" interval (47-51) has a 10 percent raise in hourly wage compared to workers aged 35-38. They have the largest negative effect in Estonia where it actually decreases the hourly wage by 17.4 percent when comparing *cohort*5 to *cohort*1. The age cohorts are significant in the pooled sample and in several countries. However, as seen from table (A5), they are not significant in all countries. Since the coefficients are significant to a little degree it is expected that the cohort differences diminished when adding more control variables.

The coefficient for female is universal negative at a 1% significance level for all countries. The female effect lowers the hourly wage by 16.4 percent in the pooled sample. Controlling for gender has the lowest effect in the Netherlands where it has a negative effect of 6.5 percent and the highest in Japan with 34.2 percent. This is not necessarily a causal effect of being a woman, but may be due to an effect of unobservable variables that more women work in lower-paid occupations than men.

The same goes for the migrant-status coefficient which is negative for every country except Japan. However, as seen from the table (5) in the descriptive statistics, there was only 0.001% of the PIAAC-survey participants with migrant status in Japan. Meaning the sample size is too small to draw concluding remarks. Having migrant status reduces the hourly wage by 8.5% in the pooled sample and the largest significant effect is found in Austria with 13.0% and the lowest in France with 4.8%.

6.2 Model 2 Controlling for formal education

As discussed above, if firm-size premiums merely reflect skill differences among workers at different firms, controlling for observable measures of skills could lead to a further reduction in the observed premiums. Thus, I first examine the impact of controlling for the "traditional" observable measure of skills, as explain in chapter (2); formal education, in addition to the variables included in the (6.1) specification.

$$lnwage_{ic} = \alpha_{c} + firmsize_{i}\theta_{c} + education_{i}\pi_{c} + experience_{i}\varphi_{c}$$
(6.2)
+
$$experience_{i}^{2}\Xi_{c} + agecohorts_{i}\rho_{c} + X_{i}\beta_{c} + jobsector_{i}\gamma_{c}$$

+
$$jobtype_{i}\vartheta_{c} + u_{ic}$$

Table 6 Effect of firm-size on wages, controlled for formal education.

	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
11to 50	0.069***	0.104***	0.010	0.087***	0.085**	0.070***	0.065*	0.074***	0.047**	0.051	0.169***
	(0.005)	(0.025)	(0.024)	(0.018)	(0.029)	(0.015)	(0.025)	(0.015)	(0.018)	(0.035)	(0.042)
51to 250	0.112***	0.140***	0.056*	0.145***	0.110**	0.078***	0.102***	0.138***	0.092***	0.162***	0.213***
	(0.006)	(0.026)	(0.024)	(0.018)	(0.035)	(0.015)	(0.027)	(0.016)	(0.019)	(0.035)	(0.045)
251to1000	0.176***	0.167***	0.110***	0.221***	0.171***	0.157***	0.167***	0.172***	0.109***	0.233***	0.287***
	(0.008)	(0.029)	(0.026)	(0.020)	(0.041)	(0.019)	(0.034)	(0.020)	(0.021)	(0.039)	(0.046)
1000+	0.231***	0.162***	0.112***	0.246***	0.185***	0.155***	0.106	0.201***	0.218***	0.344***	0.223***
	(0.016)	(0.033)	(0.032)	(0.022)	(0.053)	(0.019)	(0.054)	(0.026)	(0.026)	(0.041)	(0.056)
N	42438	1256	1371	9083	1343	2932	2354	2003	2076	1607	1215
R^2	0.401	0.556	0.404	0.493	0.464	0.456	0.460	0.588	0.502	0.502	0.415
F-stat.	141.197	10.724	7.830	45.644	6.494	23.752	6.801	29.044	20.269	27.162	10.030
	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak.	Spain	Sweden	U.K.	USA
11to 50	0.075*	0.061*	0.076*	0.075**	0.052*	0.151***	0.082*	0.034	0.029*	0.157***	0.087*
	(0.031)	(0.031)	(0.031)	(0.026)	(0.021)	(0.035)	(0.032)	(0.027)	(0.014)	(0.038)	(0.043)
51to 250	0.127***	0.128***	0.125***	0.141***	0.110***	0.141***	0.079*	0.142***	0.056***	0.173***	0.168***
	(0.035)	(0.032)	(0.035)	(0.025)	(0.022)	(0.035)	(0.033)	(0.030)	(0.015)	(0.038)	(0.042)
251to1000	0.161***	0.230***	0.187***	0.174***	0.109***	0.206***	0.133**	0.161***	0.121***	0.242***	0.257***
	(0.045)	(0.039)	(0.046)	(0.028)	(0.026)	(0.047)	(0.042)	(0.037)	(0.020)	(0.041)	(0.049)
1000+	0.228***	0.372***	0.405***	0.195***	0.158***	0.287***	0.211***	0.253***	0.115***	0.301***	0.331***
	(0.050)	(0.042)	(0.051)	(0.036)	(0.026)	(0.054)	(0.051)	(0.042)	(0.020)	(0.041)	(0.051)
Ν	1169	1747	1717	1328	1578	1002	1511	1395	1798	1916	1334
R^2	0.451	0.497	0.533	0.503	0.485	0.526	0.417	0.540	0.513	0.493	0.524
F-stat.	6.694	23.383	17.193	13.894	13.023	9.313	9.313	4.999	14.223	13.891	15.078

Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Sample: full-time employees aged 35–54. Numeracy score standardized to std. dev. 1 within each country. Experiencesq divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2 . Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001 Full table (A6) is presented in the appendix

Examining the results from table (6), we can see that adding the human capital variable *education*_{*i*}, has little effect on the firm-size premiums in any of countries. Next I will compare the results in table (6) with the results from the base model (6.1).

In the pooled estimation, the firm-size premiums are reduced by 1.0 percentage point, 1.7 percentage points 2.4 percentage points and 3.2 percentage points for the firm-size categories (11-51, 51-250, 250-1000 and 1000+), respectively. Adding these variable has the largest effect in Korea and Finland where the firm-size dummy coefficients are reduced by 1.4 - 7.1 percentage points for Korea and 1.5 - 4.7 percentage points for Finland. The smallest effect is found in the United states where the change is 1 percentage point or less for each of the firm-size categories.

For the Nordic countries I find a reduction in the firm-size premiums of 0.6 - 2.1 percentage points for Norway, a 0.6 - 1.2 percentage points for Sweden, a 0.7 - 4.5 percentage points for Denmark, and a 0.4 - 0.9 percentage points in Finland. These small reductions in firm-size premiums tells us that formal education are not the sole reasons for higher wages in larger firms, meaning the premiums must come from another unobserved variable. These results are similar to other research mention in chapter (2) and (3) Like Gibson and Stillman (2009), Troske (1999) and Albeak et al. (1998), where adding control variables for number of years of finished formal education, does not have a large effect on the firm-size premium.

Effect of other control variables

Please see table (A6) in the appendix. In this specification, where I have added the number of years of formal education an individual has, education has a unison positive significant effect on the hourly wage in every country. In the pooled sample the education coefficient is 0.036, meaning if all else is equal, one extra year of education will increase an individual's hourly wage by 3.6 percent. The education effect ranges from 2.1 percent in Sweden to 5.4 percent increase in hourly wage in United states. In Denmark the return of one additional year of education is 3.4 percent and in Norway 3.3 percent. The lowest return of education seems be in in countries with a more egalitarian wage system. Where in a country like the United States, which has a larger wage interval, the return is greater.

To further examine the hypothesis that the firm-size premiums reflects the fact that large firms hire more skilled workers, I will replace number of years of education with numeracy scores. To see if numeracy maybe is a better representation of skill-level than education.

6.3 Model 3 Controlling for numeracy scores

 $lnwage_{ic} = \alpha_{c} + firmsize_{i}\theta_{c} + numscore_{i}\omega_{c} + experience_{i}\varphi_{c}$ $+ experience_{i}^{2}\Xi_{c} + agecohorts_{i}\rho_{c} + X_{i}\beta_{c} + jobsector_{i}\gamma_{c} \qquad (6.3)$ $+ jobtype_{i}\vartheta_{c} + u_{ic}$

	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
11to 50	0.072 *** (0.01)	0.093 *** (0.03)	0.012 (0.02)	0.086 **** (0.02)	0.085 ** (0.03)	0.074 *** (0.01)	0.067 ** (0.03)	0.076 *** (0.01)	0.056 ** (0.02)	0.059 (0.03)	0.172 *** (0.04)
51to 250	0.116***	0.133***	0.059*	0.140***	0.107**	0.086***	0.104***	0.141***	0.097***	0.178***	0.223***
	(0.01)	(0.03)	(0.02)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)
251to1000	0.182***	0.152***	0.108***	0.225***	0.173***	0.160***	0.185***	0.172***	0.121***	0.229***	0.298***
	(0.01)	(0.03)	(0.03)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)	(0.04)
1000+	0.239***	0.161***	0.105**	0.259***	0.191**	0.170***	0.129*	0.203***	0.223***	0.345***	0.215***
	(0.02)	(0.03)	(0.03)	(0.02)	(0.06)	(0.02)	(0.06)	(0.03)	(0.03)	(0.04)	(0.06)
N	42912	1255	1374	9136	1348	2933	2356	2003	2090	1626	1215
R^2	0.389	0.531	0.396	0.492	0.445	0.433	0.457	0.567	0.478	0.504	0.409
F-stat.	146.286	9.161	7.177	49.522	6.083	25.744	7.724	28.279	21.210	27.724	11.813
	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak.	Spain	Sweden	U.K.	USA
11to 50	0.076*	0.067*	0.090**	0.071**	0.056**	0.153***	0.088**	0.041	0.031*	0.154***	0.079*
	(0.03)	(0.031)	(0.032)	(0.026)	(0.020)	(0.035)	(0.032)	(0.028)	(0.014)	(0.034)	(0.040)
51to 250	0.135***	0.128***	0.164***	0.139***	0.116***	0.171***	0.097**	0.146***	0.063***	0.164***	0.155***
	(0.04)	(0.032)	(0.035)	(0.026)	(0.022)	(0.034)	(0.034)	(0.031)	(0.015)	(0.035)	(0.041)
251to1000	0.161***	0.237***	0.226***	0.179***	0.126***	0.209***	0.141***	0.182***	0.122***	0.241***	0.259***
	(0.05)	(0.039)	(0.047)	(0.028)	(0.026)	(0.048)	(0.041)	(0.039)	(0.019)	(0.037)	(0.046)
1000+	0.251***	0.356***	0.447***	0.203***	0.163***	0.304***	0.221***	0.280***	0.118***	0.300***	0.308***
	(0.05)	(0.043)	(0.053)	(0.036)	(0.026)	(0.055)	(0.051)	(0.041)	(0.021)	(0.038)	(0.049)
Ν	1169	1748	1717	1328	1580	1002	1511	1395	1798	1916	1334
R^2	0.428	0.488	0.510	0.477	0.460	0.526	0.417	0.540	0.513	0.493	0.524
F-stat.	6.669	21.627	19.538	14.471	13.655	9.125	5.403	16.295	14.449	17.655	14.924

Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Sample: full-time employees aged 35–54. Numeracy score standardized to std. dev. 1 within each country. Experiencesq divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2 . Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001 Full table (A7) is presented in the appendix

In table (7), I show the effects of replacing the education variable with numeracy scores. As shown in the regression specification (6.3). Doing this does not have a great effect on reducing the firm-size premiums. In the pooled sample the firm-size premiums actually grow by a small degree compared to the regression specification where I included formal education. In the pooled sample the increase in hourly wage over the base firm-size category is now; 7.5 percent for the 11-50 employee category, 11.9 percent for the 51-250 employee category, 18.5 percent for the 251-100 employee category and 24.3 percent in the more than 1000 employee category. This is a reduction of 0.7 - 2.4 percentage points compared to the pooled sample in the base specification (6.1), and an increase of 0.2 - 0.8 percentage points compared to specification (233) which rather included education. Meaning in the pooled estimates it seems like education

controls for a, although very slightly, higher share of the firm-size premiums. Looking at each country by it-self, it varies which of formal education or numeracy that controls for most of the firm-size premiums.

In the United States numeracy scores reduces the firm-size premiums more greatly than the education variable. Meaning numeracy has a larger impact on wages in the United States than education. The difference is 2.3 percent points. In Korea the effect in the other way, education lowers the premium for the largest firm-size more greatly than numeracy does in this specification. Here education lowers the premium for the largest firm-size category 4.2 percent points more than when using numeracy as a proxy for cognitive skill. The largest firm-size effect is found in Korea where the *firmsize*5_{*i*} has an 44.7% higher hourly wage than the base *firmisze*1_{*i*}. The smallest premium for the largest firm-size category is found in Belgium with 10.5%.

Looking at the Nordic countries I find that workers in the largest firm-size category earn 17% more in Denmark, 20.3% more in Finland, 16.3% more in Norway and 11.8% more in Sweden, compared to workers in the smallest firm-size category. United States and the United Kingdom has very similar premiums for the largest firm-size category, with 30% in the for the United Kingdom and 30.8% for the United States.

Effect of other control variables

Please see full table (A7) in the appendix. This lack of impact from adding the numeracy variable is not because numeracy itself is unrelated to hourly wages. The new numeracy measure is positive and statistically significant for all of the 21 countries considered. The coefficient on numeracy in the pooled estimation suggests that a one-standard-deviation increase in numeracy skills is associated with an average increase in hourly wages of 7.9 percent across the 21 countries and is a significant positive effect in every country. This is higher than education return shown in model (6.2) One-standard-deviation increase in numeracy skills are compensated with over 10 percent in four countries, Ireland, Slovak Republic, United Kingdom and the United States, with 13.5%, 10.2%, 10% and 10.6% respectively. In three countries numeracy skill with one-standard-deviation increase the hourly wage under 5 percent; In the Czech Republic with 4.8%, in Sweden with 4.5% and the least effect in Finland, with 3.6%. I later examine if numeracy skills are compensated more greatly in larger firms.

Next I will include all of the human capital variables at my disposal and examine if they combined have a significant effect on the firm-size premiums that we observe.

6.4 Model 4 Full model

$$lnwage_{ijc} = \alpha_c + firmsize_j\theta_c + numscore_i\omega_c + education_i\pi_c$$
(6.4)

+
$$experience_i\varphi_c$$
 + $experience_i^2\Xi_c$ + $agecohorts_i\rho_c$ + $X_i\beta_c$

+ $jobsector_i \gamma_c + jobtype_i \vartheta_c + u_{ijc}$

Table 8Effect of firm-size on wages, controlled for formal education and numeracy scores

	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
11to 50	0.068***	0.098***	0.006	0.083***	0.082**	0.069***	0.064*	0.072***	0.046*	0.048	0.164***
	(0.005)	(0.025)	(0.023)	(0.018)	(0.030)	(0.015)	(0.025)	(0.014)	(0.018)	(0.035)	(0.040)
51to 250	0.108***	0.136***	0.052^{*}	0.136***	0.102**	0.075***	0.098***	0.135***	0.091***	0.161***	0.206***
	(0.006)	(0.026)	(0.024)	(0.018)	(0.035)	(0.015)	(0.027)	(0.016)	(0.019)	(0.035)	(0.043)
251to1000	0.170***	0.159***	0.100***	0.213***	0.166***	0.154***	0.165***	0.167***	0.106***	0.216***	0.273***
	(0.008)	(0.028)	(0.026)	(0.019)	(0.041)	(0.019)	(0.034)	(0.020)	(0.021)	(0.039)	(0.044)
1000+	0.222***	0.156***	0.097**	0.236***	0.189***	0.147***	0.116*	0.200***	0.213***	0.330***	0.197***
	(0.016)	(0.033)	(0.032)	(0.022)	(0.053)	(0.019)	(0.055)	(0.027)	(0.026)	(0.041)	(0.055)
N	42424	1255	1371	9080	1342	2932	2353	2003	2076	1607	1215
R^2	0.410	0.567	0.420	0.503	0.467	0.466	0.468	0.591	0.511	0.517	0.434
F-stat.	143.139	10.010	6.705	43.768	6.286	22.478	6.571	27.546	20.007	25.821	10.160
	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak.	Spain	Sweden	U.K.	USA
11to 50	0.065*	0.061*	0.077*	0.066**	0.051*	0.145***	0.081*	0.040	0.027	0.162***	0.091*
	(0.032)	(0.030)	(0.031)	(0.026)	(0.020)	(0.035)	(0.032)	(0.026)	(0.014)	(0.037)	(0.042)
51to 250	0.119***	0.123***	0.127***	0.128***	0.105***	0.140***	0.075*	0.140***	0.054***	0.169***	0.170^{***}
	(0.035)	(0.032)	(0.035)	(0.025)	(0.022)	(0.034)	(0.033)	(0.029)	(0.015)	(0.038)	(0.042)
251to1000	0.147**	0.228***	0.182***	0.166***	0.108***	0.197***	0.127**	0.160***	0.118***	0.242***	0.260***
	(0.045)	(0.038)	(0.046)	(0.028)	(0.026)	(0.047)	(0.041)	(0.036)	(0.019)	(0.040)	(0.049)
1000+	0.225***	0.344***	0.395***	0.186***	0.150***	0.278***	0.199***	0.255***	0.111***	0.294***	0.328***
	(0.050)	(0.042)	(0.050)	(0.035)	(0.026)	(0.054)	(0.051)	(0.042)	(0.020)	(0.040)	(0.050)
N	1169	1747	1717	1328	1578	1002	1511	1395	1798	1916	1334
R^2	0.458	0.506	0.537	0.514	0.493	0.533	0.430	0.546	0.519	0.513	0.530
F-stat.	6.260	20.759	16.505	12.785	11.608	8.760	4.529	14.118	13.244	14.801	14.430

Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Sample: full-time employees aged 35–54. Numeracy score standardized to std. dev. 1 within each country. Experiencesq divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2 . Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001 Full table (A8) is presented in the appendix

Table (8) displays the coefficients on the dummy variables for the four firm-size categories from specification (6.4). In this specification both numeracy scores and number of years of formal education are included. Compared to the base mode, this has a significant impact on the firm-size premiums. However, it is very small. We can observe from the f-statistics that the firm-size dummies for every country are significant at a 1% significance-level

Pooled

Looking at the pooled estimates in table (8) and comparing the firm-size dummies over the base firm-size category I find that 11 to 50 employee firms has a 6.8 percent premium, 51 to 250 employee firms has a 10.8 percent premium, 251-1000 employee firms has a 17 percent

premium and 1000+ employee firms has a 22.2 percent premium. Compared to the base specification (6.1), this is a 1.1 percentage point reduction in the premium for 11 to 50 employee firms, a 2.1 percentage point reduction for 251-1000 employee firms, a 3 percentage points reduction for 251 to 1000 employee firms, and a 4.1 percentage points reduction for 1000+ employee firms. Next I compare the results in the full model to the base specification.

Nordic countries

Examining the Nordic countries and comparing the coefficients table (8) and in the base model table (5), we can observe a premium reduction by 0.6 to 5.3 percentage points in Denmark, 0.7 to 2.8 percentage points in Norway, 0.08 to 1.6 percentage points in Sweden and 0.7 to 0.5 percentage points in Finland.

English speaking countries

In the English speaking countries, we can observe that the firm-size premium of workers in 1000+ employee firms, have been reduced by, only 0.6 percentage points in the United States, 1.5 percentage points in the United Kingdom, 4.7 percentage points in Canada and 7.3 percentage points in Ireland. Education and numeracy seems to be more important for wages in the 1000+ employee firms in Ireland than in the US. The results for Canada, and the United Kingdom is similar to the results of Gibson and Stillman (2009) Where they found little effect of controlling for education and a cognitive skill measurement. However, they used a literacy variable which composed of prose, document and numeracy literacy. Making it difficult to compare to my results, which use numeracy scores from the PIAAC-survey, which was calculated differently. Contrast to my data where the United States has one of the largest firm-size premiums, Gibson and Stillman (2009) does not find any significant firm-size premium for the US, using their IALS-data.

Continental west Europe

Examining the west European countries, I find firm-size premiums to be; 0.6 to 3.7 percentage point reduction in Germany. 0.1 to 1.4 percentage points in Austria, 1.3 to 3.2 percentage points in Belgium, 1.4 to 2 percentage points in France, 2.9 to 3.3 in Italy, 2.1 to 3.9 in the Netherlands, 1.0 to 8.1 percentage points in Spain.

Former communist countries

Looking that the former communist countries and comparing it to the base model, I find that the firm-size premiums are reduced by; (-0.5) to 1.8 percentage points in the Czech Republic,

0.1 to 0.4 in Estonia, 1.6 to 4.6 in Poland and 1.0 to 4.3 percentage points in the Slovak Republic.

Asian countries

In the Asian countries, when comparing table (5) and table (8), I find that the firm-size premiums are reduced by 0.9 to 6.2 percentage points in Japan and 1.3 to 8.1 percentage points in Korea when controlling for number of year of formal education and numeracy. The largest reduction is found in Korea with 8.1 percent in the largest firm-size category. This is thought to be expected since Korea had the largest premium.

These are small change from the first specification. There is a small reduction in the pooled sample, but it cannot support the hypothesis that firm-size premiums solely arise from workers being more skilled in larger firms. At least not with the current observable skill measurements. Adding these additional control variables in each of these alternative specifications has little qualitative impact on the firm-size premium in any country.

Effect of control variables

Please see full table (A8) in the appendix. The numeracy and education coefficients has an econometrical impact on each other. In the pooled sample of table (8) we can see that numeracy coefficient has been reduced to 0.056 from 0.08 in specification (6.4), while education coefficient has been reduced to 0.03 from 0.036 in specification (6.3). On average, the coefficients for numeracy and education drop about one-quarter when both variables are included in the wage function.

Adding the education and numeracy variables has reduced the disadvantage of women in the pooled sample by only 2 percentage points from model (6.1), meaning there are other unobservable variables the differences in education that negatively affect women. There is still an earnings disadvantage of women of 20% and more in six countries (Estonia, Japan, Korea, and the Slovak Republic). The same can be said for migrant status.

Since there is small reduction for the size premiums, the next step is to test the interaction between these variables. A potential explanation for the observed size-related variation in wages is that the return to numeracy or education increases with firm-size. A simple test of this hypothesis is to interact the schooling and numeracy score variables with the firm-size variable. This will be done in chapter (6.5).

6.5 Model 5 Interaction between firm-size and education

 $lnwage_{ijc} = \alpha_{c} + firmsize_{j}\theta_{c} + education_{i}\pi_{c} + experience_{i}\varphi_{c}$ $+ experience_{i}^{2}\Xi_{c} + (firmsize_{j} * education_{i})\Phi_{c}$ $+ agecohorts_{i}\rho_{c} + X_{i}\beta_{c} + jobsector_{i}\gamma_{c} + jobtype_{i}\vartheta_{c} + u_{ijc}$

(6.5)

Table 9Effect of the Interaction between firm size and education on wages

	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
11to 50	-0.049	-0.002	-0.009	-0.075	0.384*	0.021	-0.136	0.100	0.054	-0.477*	0.470^{*}
	(0.030)	(0.111)	(0.119)	(0.092)	(0.166)	(0.077)	(0.126)	(0.071)	(0.059)	(0.195)	(0.222)
51to 250	-0.004	0.070	-0.020	0.023	0.306	-0.116	-0.213	0.242***	0.124*	-0.101	0.289
	(0.034)	(0.117)	(0.112)	(0.098)	(0.163)	(0.081)	(0.133)	(0.073)	(0.059)	(0.201)	(0.227)
251to1000	0.010	0.185	-0.143	0.101	0.629**	0.131	-0.157	0.243**	-0.031	-0.101	0.509*
	(0.045)	(0.128)	(0.134)	(0.107)	(0.220)	(0.102)	(0.160)	(0.085)	(0.070)	(0.190)	(0.258)
1000+	0.115	0.050	0.021	0.247^{*}	-0.059	0.045	-0.564*	0.231*	0.229*	0.468*	0.036
	(0.055)	(0.148)	(0.142)	(0.117)	(0.281)	(0.099)	(0.241)	(0.103)	(0.095)	(0.195)	(0.333)
firm2*educ	0.009***	0.009	0.002	0.012	-0.023	0.004	0.017	-0.002	-0.001	0.040**	-0.021
	(0.002)	(0.009)	(0.009)	(0.007)	(0.012)	(0.006)	(0.010)	(0.005)	(0.005)	(0.014)	(0.014)
firm3*educ	0.009**	0.006	0.006	0.009	-0.015	0.015*	0.026^{*}	-0.008	-0.003	0.020	-0.006
	(0.003)	(0.009)	(0.009)	(0.007)	(0.012)	(0.006)	(0.010)	(0.006)	(0.005)	(0.015)	(0.015)
firm4*educ	0.013**	-0.001	0.020	0.009	-0.034*	0.002	0.027^{*}	-0.006	0.011	0.025	-0.015
	(0.003)	(0.010)	(0.010)	(0.008)	(0.017)	(0.008)	(0.012)	(0.006)	(0.006)	(0.014)	(0.016)
firm5*num	0.009*	0.009	0.007	0.001	0.019	0.009	0.054**	-0.002	-0.001	-0.006	0.010
	(0.008)	(0.011)	(0.011)	(0.008)	(0.020)	(0.007)	(0.019)	(0.007)	(0.008)	(0.014)	(0.020)
N	42438	1256	1371	9083	1343	2932	2354	2003	2076	1607	1215
R^2	0.059	0.568	0.421	0.504	0.464	0.467	0.462	0.590	0.511	0.520	0.441
F-stat.	4.942	0.517	1.253	1.204	2.287	1.932	2.933	0.682	2.107	6.155	1.320
	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak.	Spain	Sweden	U.K.	USA
11to 50	0.013	-0.093	-0.091	-0.208	-0.072	0.154	0.110	-0.059	-0.020	0.151	-0.117
	(0.098)	(0.194)	(0.126)	(0.147)	(0.119)	(0.165)	(0.178)	(0.084)	(0.079)	(0.211)	(0.202)
51to 250	0.163	0.007	-0.171	-0.202	0.009	0.195	0.126	0.168	-0.026	0.016	-0.049
	(0.108)	(0.207)	(0.147)	(0.138)	(0.124)	(0.154)	(0.177)	(0.100)	(0.075)	(0.209)	(0.206)
251to1000	0.064	0.096	-0.172	-0.157	0.104	0.147	0.251	0.106	0.047	0.062	0.053
	(0.136)	(0.241)	(0.183)	(0.152)	(0.136)	(0.202)	(0.249)	(0.135)	(0.105)	(0.220)	(0.299)
1000+	0.350*	0.456	-0.387	-0.109	-0.074	0.441	0.533	0.448***	0.070	-0.164	0.266
	(0.176)	(0.266)	(0.234)	(0.208)	(0.147)	(0.245)	(0.286)	(0.114)	(0.106)	(0.216)	(0.247)
firm2*educ	0.006	0.012	0.014	0.021	0.009	-0.000	-0.002	0.008	0.004	0.001	0.015
	(0.008)	(0.015)	(0.010)	(0.011)	(0.008)	(0.013)	(0.013)	(0.007)	(0.006)	(0.016)	(0.015)
firm3*educ	-0.003	0.010	0.023*	0.026^{*}	0.007	-0.004	-0.004	-0.002	0.007	0.013	0.016
	(0.009)	(0.016)	(0.011)	(0.010)	(0.008)	(0.012)	(0.013)	(0.008)	(0.006)	(0.016)	(0.015)
firm4*educ	0.009	0.010	0.028^{*}	0.025^{*}	0.001	0.005	-0.009	0.004	0.006	0.014	0.015
	(0.011)	(0.017)	(0.013)	(0.011)	(0.009)	(0.016)	(0.019)	(0.011)	(0.008)	(0.017)	(0.020)
firm5*num	-0.010	-0.004	0.056***	0.023	0.015	-0.011	-0.024	-0.014	0.004	0.034*	0.006
	(0.014)	(0.019)	(0.015)	(0.015)	(0.010)	(0.018)	(0.021)	(0.009)	(0.008)	(0.017)	(0.017)
N	1169	1750	1720	1328	1578	1003	1512	1395	1798	1916	1334
R^2	0.456	0.506	0.541	0.511	0.491	0.531	0.432	0.545	0.520	0.515	0.534
F-stat.	0.719	0.368	3.743	1.768	0.932	0.200	0.368	1.988	0.339	1.976	0.427

Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Sample: full-time employees aged 35–54. Numeracy score standardized to std. dev. 1 within each country. Experiencesq divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2 . Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001 Full table (A9) is presented in the appendix

Here I have included the $(firmsize_j * education_i)\Phi_c$, which represents the interaction between firm-size dummy variables and formal education level of an individual. From this I can examine if the monetary gain from education is rewarded different in larger firms. The f-statistics the table (9) represents the following hypothesis:

$$H_0: \Phi_c = 0 \iff H_0: \Phi_2 = \Phi_3 = \Phi_4 = \Phi_5 = 0$$
$$H_A: \Phi_c \neq 0$$

Meaning I test if all four of the interaction terms are significantly different from zero, using the f-statistics. For the pooled sample, the coefficient of the schooling-size interaction term is significant. The findings are in line with results for the US pointing to a higher return to schooling in larger firms (Brown and Medoff, 1989; Idson and Feaster, 1990; Pearce, 1990). The increased return is however very small, 0.9 percent. With a F-test of F(4,42438) = 4.94and a critical value at a 1% significance-level ($F_{crit} = 2.576$) H_o can be dismissed if $F_{obs} > F_{crit}$, 4.94 > 2.576 I can dismiss the zero hypothesis. However, almost none of the country-specific f-statistics are larger than the critical value. So in most countries it does not seem to be a significant higher wage reward of formal education in larger firms. A non-significant higher return of education in large firms are in line with findings of (Albaek et. al, 1998; Main and Reilly, 1993). Albaek et. al, (1998) found no significant higher return of formal education when looking at Norway, Sweden, Finland and Denmark. Nor do I. Main and Reilly (1993), does not find any significant differences in returns to education across different firm-size categories for the United Kingdom. In my data for the United Kingdom, I find the interaction between the largest firm size category and education to be 3.4% higher compared to the smallest firm size category at a 10% significance-level. I, however, as seen from the f-statistics, do not find the results to be significant when testing all the interaction terms combined.

Interestingly I find that the largest significant reward of education in larger firms is in Korea. Where education in the largest firm-size category is rewarded 5.6 percent more than in the smallest, Korea is also the country I find that controlling for education has the largest effect on the firm-size premiums in the whole sample

Next is to examine if there is a significant interaction between the between numeracy and firmsize on wages. I will examine if there is a higher wage reward of numeracy skills in larger firms.

6.6 Model 6 Interaction between firm-size and numeracy

 $lnwage_{ic} = \alpha_{c} + firmsize_{i}\theta_{c} + numscore_{i}\omega_{c} + experience_{i}\varphi_{c}$ $+ experience_{i}^{2}\Xi_{c} + (firmsize_{j} * numscore_{i})\partial_{c}$ $+ agecohorts_{i}\rho_{c} + X_{i}\beta_{c} + jobsector_{i}\gamma_{c} + jobtype_{i}\vartheta_{c} + u_{ic}$ (6.7)

Table 10 Effect of the Interaction between firm size and numeracy on wages

	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
11to 50	0.073***	0.095***	0.009	0.085***	0.083**	0.074***	0.069**	0.076***	0.055**	0.060	0.172***
	(0.006)	(0.026)	(0.024)	(0.018)	(0.031)	(0.015)	(0.025)	(0.015)	(0.019)	(0.035)	(0.039)
51to 250	0.118***	0.140***	0.055*	0.138***	0.109**	0.080***	0.103***	0.140***	0.099***	0.180***	0.219***
	(0.007)	(0.027)	(0.024)	(0.018)	(0.037)	(0.016)	(0.028)	(0.016)	(0.019)	(0.035)	(0.042)
251to1000	0.181***	0.157***	0.106***	0.222***	0.177***	0.161***	0.191***	0.172***	0.114***	0.231***	0.276***
	(0.009)	(0.029)	(0.027)	(0.020)	(0.042)	(0.020)	(0.035)	(0.022)	(0.022)	(0.039)	(0.044)
1000+	0.179***	0.154***	0.086**	0.265***	0.197***	0.139***	0.129*	0.209***	0.209***	0.360***	0.223***
	(0.037)	(0.035)	(0.033)	(0.023)	(0.059)	(0.024)	(0.056)	(0.030)	(0.026)	(0.045)	(0.062)
firm2*num	0.019**	0.031	0.039	0.012	0.009	0.015	0.045	0.005	0.019	0.063	-0.15**
	(0.006)	(0.022)	(0.026)	(0.019)	(0.032)	(0.017)	(0.026)	(0.016)	(0.020)	(0.041)	(0.047)
firm3*num	0.013	0.030	0.042	0.012	0.024	0.036*	0.048	-0.011	0.020	-0.004	-0.125*
	(0.007)	(0.023)	(0.026)	(0.018)	(0.029)	(0.018)	(0.028)	(0.017)	(0.020)	(0.039)	(0.054)
firm4*num	0.021**	0.037	0.046	0.010	0.020	0.015	0.025	0.002	0.042	0.013	-0.073
	(0.007)	(0.026)	(0.029)	(0.019)	(0.033)	(0.021)	(0.035)	(0.021)	(0.022)	(0.041)	(0.052)
firm5*num	0.019*	0.064*	0.064*	-0.013	0.030	0.073**	-0.009	-0.036	0.061*	-0.013	-0.115
	(0.009)	(0.031)	(0.033)	(0.021)	(0.047)	(0.026)	(0.046)	(0.041)	(0.027)	(0.046)	(0.068)
Ν	42438	1256	1371	9083	1343	2932	2354	2003	2076	1607	1215
R^2	0.059	0.568	0.421	0.504	0.464	0.467	0.462	0.590	0.511	0.520	0.441
F-stat.	81.961	8.259	10.943	14.420	1.204	13.353	9.980	3.053	10.517	10.707	2.965
	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak.	Spain	Sweden	U.K.	USA
11to 50	0.072*	0.070^{*}	0.093**	0.074**	0.054**	0.151***	0.086**	0.038	0.030*	0.156***	0.070
	(0.033)	(0.031)	(0.031)	(0.026)	(0.020)	(0.036)	(0.033)	(0.029)	(0.014)	(0.035)	(0.039)
51to 250	0.127***	0.127***	0.161***	0.134***	0.113***	0.166***	0.099**	0.137***	0.060***	0.163***	0.153***
	(0.037)	(0.032)	(0.035)	(0.026)	(0.022)	(0.036)	(0.034)	(0.031)	(0.015)	(0.035)	(0.040)
251to1000	0.152**	0.230***	0.200***	0.176***	0.126***	0.203***	0.126**	0.162***	0.118***	0.232***	0.260***
	(0.049)	(0.041)	(0.049)	(0.029)	(0.027)	(0.049)	(0.041)	(0.040)	(0.020)	(0.037)	(0.047)
1000+	0.233***	0.368***	0.398***	0.200***	0.168***	0.303***	0.236***	0.264***	0.121***	0.311***	0.305***
	(0.050)	(0.051)	(0.056)	(0.037)	(0.028)	(0.054)	(0.051)	(0.048)	(0.020)	(0.040)	(0.053)
firm2*num	-0.018	-0.014	0.067*	0.005	0.018	0.038	0.007	0.015	-0.001	0.018	0.075
	(0.035)	(0.028)	(0.031)	(0.026)	(0.019)	(0.036)	(0.037)	(0.030)	(0.016)	(0.032)	(0.044)
firm3*num	-0.014	0.001	0.098**	0.043	0.018	0.037	-0.012	0.025	0.019	0.046	-0.036
	(0.034)	(0.029)	(0.035)	(0.026)	(0.021)	(0.036)	(0.042)	(0.034)	(0.016)	(0.033)	(0.046)
firm4*num	-0.010	0.036	0.114*	0.049	0.013	0.027	0.042	0.041	0.022	0.067*	-0.026
	(0.052)	(0.038)	(0.049)	(0.027)	(0.025)	(0.049)	(0.047)	(0.049)	(0.020)	(0.034)	(0.055)
firm5*num	-0.006	-0.007	0.129**	0.037**	-0.002	-0.011	-0.034	0.032	-0.009	0.010	0.012*
	(0.045)	(0.037)	(0.046)	(0.032)	(0.025)	(0.052)	(0.055)	(0.045)	(0.019)	(0.037)	(0.055)
N	1169	1750	1720	1328	1578	1003	1512	1395	1798	1916	1334
R^2	0.456	0.506	0.541	0.511	0.491	0.531	0.432	0.545	0.520	0.515	0.534
F-stat.	1.178	4.315	7.885	8.260	6.620	3.367	5.838	2.209	5.536	11.843	5.848

Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Sample: full-time employees aged 35–54. Numeracy score standardized to std. dev. 1 within each country. Experiencesq divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; \mathbb{R}^2 refers to within-country \mathbb{R}^2 . Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001 Full table (A10) is presented in the appendix

Here I have included the $(firmsize_j * numscore_i)\partial_c$, which represents the interaction between firm-size dummy variables and numeracy test scores of an individual. From this I can see if the monetary gain from numeracy skills are rewarded differently in larger firms. Using an F-test I will test if the interaction between numeracy and firm-sizes are significantly different from zero, with the hypothesis:

$$H_0: \partial_c = 0 \iff H_0: \partial_2 = \partial_3 = \partial_4 = \partial_5 = 0$$
$$H_A: \partial_c \neq 0$$

In the pooled sample, this gives a F-value of F(4, 42872) = 81.9 and a critical value at a 1% significance-level ($F_{crit} = 2.576$) H_o can be dismissed if $F_{obs} > F_{crit}$ 81.9 > 2.576. With a large margin I can dismiss the zero hypothesis. In the pooled sample we observe that the larger firmsize the higher numeracy is rewarded. The coefficients for *firmsize5* * *numeracy_i* is 0.019. Meaning one-standard deviation increase of numeracy is rewarded with 1.% more that in *firmsize*1.

I can dismiss the zero hypothesis in every country except, Italy, Spain and the Czech Republic. There is a wage effect of the interaction between numeracy skills and firm-size in almost all countries. In the separate countries, interaction-coefficients vary in positive and negatives and in significance.

As with education, the largest positive effect is found in Korea with 12.9% higher numeracy return in firms with more than 1000 employees compared to firm with 1 to 10 employees. The largest negative effect is found in Ireland where, on average, individuals in the 11 to 50 employee firm category is rewarded 14% less for one-standard deviation increase in numeracy scores compared to workers in the 1 to 10 employee firm category.

6.7 Model 7 Public vs. Private

Until now I have studied the firm-size wage premiums for the whole sample and have not differentiated between groups. By differentiate the sample for workers in the private and public sector I can examine the differences in the firm-size wage effect for government and private workers. Previous consensus has been that public workers are paid less than their private counterparts. A growing number of research have found this to be false for many countries. De De Castro et, al (2013) find that in the European Union public sector employees are found to have on average higher wages than comparable workers in the private sector in 2010, even after controlling for the level of educational attainment. Giving potential interest to examine the firm-size premiums are prevalent in both sectors. Using the specification of model (6.4), I will examine the differences between private and public firm-size premiums.

	Private	Public	Private	Public	Private	Public	Private	Public	Private	Public
	Pooled	Pooled	Austria	Austria	Belgium	Belgium	Canada	Canada	Czech.	Czech.
11to 50	0.063***	0.044***	0.113***	0.037	0.003	-0.049	0.061**	0.094**	0.088*	0.064
	(0.006)	(0.011)	(0.030)	(0.048)	(0.028)	(0.051)	(0.021)	(0.035)	(0.039)	(0.043)
51to 250	0.111***	0.072***	0.149***	0.091	0.040	-0.006	0.127***	0.110**	0.071	0.189***
	(0.006)	(0.012)	(0.032)	(0.050)	(0.029)	(0.049)	(0.022)	(0.035)	(0.049)	(0.043)
251to1000	0.188***	0.090***	0.166***	0.127^{*}	0.099**	0.039	0.218***	0.134***	0.222***	0.011
	(0.011)	(0.012)	(0.034)	(0.054)	(0.031)	(0.054)	(0.024)	(0.035)	(0.052)	(0.056)
1000+	0.252***	0.126***	0.198***	0.070	0.091*	0.016	0.266***	0.147***	0.187**	0.233**
	(0.021)	(0.018)	(0.039)	(0.067)	(0.039)	(0.063)	(0.031)	(0.036)	(0.067)	(0.090)
N	26571	14517	825	393	889	431	5252	3416	894	424
R^2	0.428	0.361	0.587	0.584	0.457	0.443	0.500	0.448	0.477	0.591
F-stat.	115.563	14.486	8.575	1.972	4.441	1.258	29.602	4.829	6.399	6.107
	Private	Public	Private	Public	Private	Public	Private	Public	Private	Public
	Denmark	Denmar	x Estonia	Estonia	Finland	Finland	France	France	Germany	Germany
11to 50	0.063***	0.062^{*}	0.070^{*}	0.057	0.059**	0.078***	0.037	0.041	0.070	-0.123
	(0.018)	(0.025)	(0.031)	(0.040)	(0.019)	(0.022)	(0.020)	(0.042)	(0.040)	(0.064)
51to 250	0.078***	0.073**	0.095**	0.131**	0.141***	0.113***	0.080***	0.086*	0.185***	-0.006
	(0.019)	(0.027)	(0.034)	(0.041)	(0.021)	(0.024)	(0.021)	(0.041)	(0.042)	(0.058)
251to1000	0.165***	0.138***	0.195***	0.160**	0.189***	0.125***	0.112***	0.073	0.274***	-0.036
	(0.024)	(0.032)	(0.045)	(0.052)	(0.027)	(0.032)	(0.025)	(0.042)	(0.046)	(0.063)
1000+	0.172***	0.113***	0.028	0.228***	0.239***	0.150***	0.255***	0.142**	0.389***	0.006
	(0.025)	(0.032)	(0.085)	(0.068)	(0.037)	(0.034)	(0.031)	(0.050)	(0.048)	(0.077)
N	1628	1248	1493	819	1176	772	1434	590	1126	402
R^2	0.488	0.446	0.454	0.595	0.589	0.646	0.537	0.519	0.548	0.504
F-stat.	17.278	5.681	4.998	5.644	19.539	7.426	18.438	2.940	23.927	2.084

Table 11 Firm-size premiums differences in private and public sector

	Private Ireland	Public Ireland	Private Italy	Public Italy	Private Japan	Public Japan	Private Korea	Public Korea	Private Netherl.	Public Netherl
11to 50	0.107*	0.210*	0.076*	0.003	0.055	-0.082	0.068*	-0.002	0.070*	0.052
	(0.043)	(0.095)	(0.036)	(0.066)	(0.033)	(0.135)	(0.034)	(0.110)	(0.030)	(0.056)
51to 250	0.138**	0.259** 0.126**		0.015	0.118***	0.053	0.098** -0.007		0.122***	0.127**
	(0.053)	(0.090)	(0.042)	(0.064)	(0.035)	(0.141)	(0.038) (0.113)		(0.032)	(0.048)
251to1000	0.259***	0.253* 0.161**		-0.009	0.254***	-0.066	0.148** 0.063		0.176***	0.141**
	(0.049)	(0.102)	(0.061)	(0.070)	(0.042)	(0.146)	(0.055)	(0.116)	(0.035)	(0.051)
1000+	0.256***	0.125 0.218*		0.082	0.391***	-0.017	0.398*** 0.180		0.211***	0.141**
	(0.064)	(0.111)	(0.060)	(0.077)	(0.045) (0.148)		(0.060) (0.125)		(0.052)	(0.053)
N	737	452 819		345	1419	264	1339 312		830	434
R^2	0.471	0.455	0.472	0.433	0.524	0.428	0.515	0.601	0.522	0.545
F-stat.	8.281	2.732	4.439	0.610	22.838	1.148	11.336	1.446	8.265	3.276
	Private		blic	Private	Public	Privat		ıblic	Private	Public
	Norway			Poland	Poland		Slovak. Slo		Spain	Spain
11to 50	0.056*	-0.011		0.143***	0.113	0.124**	* 0.0)13	0.005	-0.022
	(0.024)	(0.0	041)	(0.043)	(0.071)	(0.041)) (0.	047)	(0.029)	(0.049)
51to 250	0.136***	0.013		0.167***	0.062	0.132**	-0.	.001	0.161***	0.015
	(0.027)	(0.0)43)	(0.042)	(0.070)	(0.044)) (0.	052)	(0.037)	(0.051)
251to1000	0.144***	0.010		0.240***	0.084	0.151**	0.1	129	0.175***	0.016
	(0.034)	(0.045)		(0.061)	(0.080)	(0.048) (080)	(0.047)	(0.059)
1000+	0.157***	0.088		0.358***	0.096	0.239**	•* 0.1	112	0.234***	0.095
	(0.037)	(0.045)		(0.074)	(0.096)	(0.060)) (0.093)		(0.063)	(0.064)
V	923	637		625	370	994	495		926	444
R ²	0.507	0.501		0.518	0.581	0.445	0.498		0.515	0.518
F-stat.	8.647	4.375		8.125	1.044	4.735	4.735 1.		9.463	1.277
		Priva	te	Public	Privat	e Pu	blic	Private	Publ	ic
		Swede		Sweden	U.K.		.К.	USA	USA	
11to 5	11to 50		0.047*		0.024 0.149**		.016	0.090	0.10	2
		(0.020))	(0.017)	(0.044		070)	(0.050)	(0.08	5)
51to 250		(0.020) 0.074***		0.048**	0.135*		.005	0.187***	0.072	
		(0.021)		(0.018)	(0.044			(0.049)	(0.078)	
251to1000 1000+		0.151***		0.099***	0.212**		036	0.268***	0.140	
		(0.026) 0.183 ***		(0.026)	(0.048		077)	(0.060)	(0.08	
				0.053*	0.270**	· · · · ·	086	0.294***	0.268	·
		(0.030)		(0.026)	(0.054		072)	(0.060)	(0.099)	
N		978	/	794	1064	· · · ·	70	863	360	,
R^2		0.528		0.511	0.557		520	0.579	0.47	
F-stat		12.960		4.000	7.589		.90	8.923	2.118	

Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Sample: full-time employees aged 35–54. Numeracy score standardized to std. dev. 1 within each country. Experiencesq divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2 . Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001 Full table (A11 and A12) is presented in the appendix

Examining table (11), I find large differences in the public and private sector in almost every country. In the pooled estimation we can observe a 12,6 percentage point difference in the firm-size premiums between private and public, in the largest firm-size category. This seems to be universal for every country. The firm-size premiums in the public sector are lower than in the private sector. Far less of the firm-size coefficients in the public sector estimation are

statistically significant. This is to be expected since wages are usually more rigid in the public sector. It may also be possible that workers in the public sector are compensated other ways than by wages. Public workers are known in some countries to have better benefits, working conditions and may be more likely to unionize. As discussed in chapter (2), a reason for the firm-size premiums may be compensation for less desirable work conditions. As this is an unobservable variable this is just speculation. Looking at the Scandinavian countries, Norway does not have a significant firm-size wage premium in the public sector. Denmark and Sweden has a 5.9% and a 13% difference between the sectors in the 1000+ employee firm category, respectively.

Looking at table (A8) and (A9) in the appendix, we can see that there is a greater wage return of numeracy in the private sector. In the pooled sample we can observe that one-standard deviation increase in numeracy is 1.4 percentage points more rewarded in the private sector. Numeracy have a higher return for workers in the private sector in every country except Belgium and Italy. The largest difference is found the United States where workers in the private sector has a return of 6.4 percent of one-standard deviation increase of numeracy and no significant return of numeracy in the public sector. The lowest difference is found in Norway, where the return only differs by 0.6 percent between the two sectors.

Return of education also differs between the public and private sector. In the pooled sample, one additional year of education is rewarded by 0.6% more in the public sector. Every country except for the Czech Republic, Japan, the Slovak Republic and the United Kingdom, has a higher return of education in the public sector. The largest difference is also here found in the United States, where public workers has, on average, a 3.6% higher return of one additional year of education. Norway also again has the lowest difference, with only 0.2 percent between the two sectors.

6.8 Model 8 Numeracy scores and firm-size

A final question worth examining is to confirm what I observed in table (3), whether workers with higher average skill levels are actually sorting into larger firms. I will compare my results to Gibson and Stillman (2009) and see if I get the same results using the PIAAC-data and numeracy as the skill variable. To examine this, I regress standardized numeracy scores on a set of dummy variables indicating the firm-size category:

$$lnnumscore_{ic} = \alpha_c + firmsize_i\theta_c + u_{ic}$$
(38)

	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
11to 50	0.099***	0.251	0.286*	0.064	0.125	0.172	0.083	-0.038	0.120	0.358*	0.152
	(0.019)	(0.132)	(0.118)	(0.068)	(0.158)	(0.090)	(0.073)	(0.098)	(0.085)	(0.141)	(0.113)
51to 250	0.157***	0.251*	0.213	0.097	0.201	0.224*	0.165*	0.175	0.129	0.359*	0.190
	(0.016)	(0.127)	(0.119)	(0.070)	(0.156)	(0.090)	(0.082)	(0.099)	(0.092)	(0.144)	(0.130)
251to1000	0.223***	0.525***	0.296*	0.208**	0.133	0.239*	0.352***	0.152	0.133	0.476**	0.172
	(0.027)	(0.132)	(0.128)	(0.074)	(0.221)	(0.106)	(0.098)	(0.123)	(0.099)	(0.158)	(0.121)
1000+	0.308***	0.531**	0.594***	0.246**	-0.808	0.373***	0.250	0.281^{*}	0.282**	0.613***	0.446**
	(0.037)	(0.168)	(0.124)	(0.083)	(0.647)	(0.106)	(0.149)	(0.132)	(0.109)	(0.148)	(0.141)
N	26925	789	887	5440	833	1904	1470	1158	1258	996	843
R^2	0.008	0.029	0.025	0.006	0.033	0.010	0.009	0.008	0.006	0.027	0.013
F-stat.	24.660	5.190	6.718	3.607	0.950	3.356	3.761	2.621	1.701	4.714	2.538
	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak.	Spain	Sweden	U.K.	USA
11to 50	0.399***	-0.002	-0.020	0.244	0.052	0.174	0.071	0.038	0.052	-0.146	0.063
	(0.120)	(0.099)	(0.101)	(0.132)	(0.099)	(0.152)	(0.104)	(0.088)	(0.114)	(0.132)	(0.128)
51to 250	0.282^{*}	0.204^{*}	0.153	0.222	0.172	0.285	-0.015	0.255**	0.147	0.062	0.107
	(0.121)	(0.101)	(0.093)	(0.127)	(0.099)	(0.157)	(0.106)	(0.088)	(0.113)	(0.120)	(0.120)
251to1000	0.272	0.384***	0.151	0.293*	0.318**	0.333	-0.013	0.225	0.347**	-0.054	0.241
	(0.249)	(0.113)	(0.121)	(0.139)	(0.108)	(0.178)	(0.145)	(0.126)	(0.127)	(0.154)	(0.127)
1000+	0.207	0.606***	0.457***	0.297^{*}	0.307**	0.465*	-0.031	0.051	0.380**	0.017	0.391**
	(0.147)	(0.106)	(0.108)	(0.150)	(0.105)	(0.200)	(0.178)	(0.147)	(0.126)	(0.130)	(0.123)
N	773	1089	915	868	1222	556	1008	964	1086	1445	968
R^2	0.019	0.036	0.020	0.007	0.014	0.014	0.001	0.012	0.016	0.006	0.017
F-stat.	2.913	12.290	5.389	1.351	4.288	1.767	0.300	2.891	4.301	1.054	4.386

Table 12 Effect of firm-size on numeracy scores.

Least squares regressions weighted by sampling weights. Dependent variable: log numeracy scores. Sample: full-time employees aged 35–54. Numeracy score standardized to std. dev. 1 within each country. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2 . Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001 Full table (A13) is presented in the appendix

The pooled results show an increasing average numeracy score in the different firm-size categories. With 9.9% and 15.7% higher standardized numeracy scores for the two categories above the smallest firm-size. This jumps to 22.3% and 30.8% for the two largest firm-size categories. Giving some evidence for the sorting of higher skilled employees hypothesis.

Chapter 6 Empirical results

From the f-statistics in table (12) we can see that there is a significant firm-size premium of numeracy scores in all countries, except the Czech Republic, France, the Netherlands, Poland, the Slovak Republic and the United Kingdom. Although not significant for every firm-size dummy. We can see from R-squared that the variation in firm-size dummies explains little of the variation of numeracy scores.

Viewing the Nordic countries, we can observe that workers in the 1000+ employee firm-size category has on average, 30% higher standardized numeracy scores compared to workers in 1-10 employee firm-size category in Norway, 38% higher in Sweden, 37% higher in Denmark and 28% higher in Finland. Similar results for the Nordic countries, but this may be expected from the inhabitants of these countries being homogeneous is many ways.

Interestingly I find that many of the countries with the highest firm-size wage premiums also have one of the firm-size numeracy premiums. In Germany subjects working in 1000+ employee firms had, on average, a 61.3% higher standardized numeracy scores than subjects in 1-10 employee firms, and in Japan the difference is 60.6%

Gibson and Stillman (2009) did only find workers in the English speaking countries, with higher test scores, sorted into larger firms. I find this sorting in almost all countries. However, they used a literacy variable which composed of prose, document and numeracy literacy. Making it difficult to compare with my results, which use the numeracy tests preformed in the PIAAC-survey, which were calculated differently.

Summary: In this chapter I have, using the PIAAC-survey presented, clear evidence of the previously observed positive relationship between wages and firm-size. In addition to normal control variables, I have controlled for education and numeracy test scores, which I find to have some, but very little effect on the average firm-size premiums. I have tested the relationship between education and numeracy with firm-sizes. I find that education is not significantly rewarded any differently in larger firms. I do find to some degree that numeracy is rewarded differently in larger firms. I also find that, when compared to the public sector, private sectors have larger firm-size premiums in every country. Last, I find some evidence of larger firm's employ higher quality labor, measured by numeracy test scores.

Chapter 7 Conclusion

Chapter 7 Conclusion

Firm-size premiums have been widely observed since More (1911) and data show that it is still prevalent today. My data shows that almost all countries have an increasing linear return of firm-size.

The research reported in this thesis has aimed to test the hypothesis that the higher wage of workers in larger firms reflects differences in unobserved labor-quality. In contrast to most previous literature, which attempts to proxy for skills by using variables that are more properly considered as inputs into skill production, more direct measures of skills were used here. Data from the "Programme for the International Assessment of Adult Competencies" survey gave the test results on individual's cognitive skills. These tests measure skills previously unobserved by econometricians, but may have been observed by employers when making their wage offers.

My result confirms earlier research that using formal education as the control variable and as a proxy for skill, does little to impact the firm-size premiums we observe. Utilizing and controlling for numeracy, which is a direct measurement of cognitive skill, does not have a great impact on the firm-size premium neither. Using both these variables as a measurement of skill, I find, in the pooled sample, that the firm-size premium of workers who are employed in firms with more than 1000 employees, is reduced by only 4.1 percentage points. From 26.2% in the base model to 22.2% in the full model. My results cannot give support to the hypothesis that firm-size premiums arise from differentials in labor-quality.

The largest firm-size premiums are found in countries with the largest wage spread and interestingly this coincides with them having a more capitalistic economic system, compared to the rest of the sample. The smallest firm-size premiums are found in the Nordic countries and some of the former communistic countries, which also have a relative low spread of wages.

I further modified the model and added interaction terms for both firm-size and numeracy and firm-size and education. From this I examined possible differences in how these human capital measurements are rewarded in larger firms. Few of the countries had significant differences in the return of education in larger firms. My results show that numeracy have a significantly different return in larger firms. This is almost universal in every country.

I show that firm-size premiums are larger in the private sector than in the public sector. A large number of countries do not have a significant firm-size premium in the public sector. This could be because public sector employees often are subject to more rigid and less flexible wage systems.

A key inference from these results is that higher salaries in larger firms cannot solely be explained by workers in larger firms having, on average, higher numeracy skill or longer formal education. There are unobserved variables that correlate with firm-size that cause the higher wages. Overall, despite the more comprehensive data available to this thesis, a large part of the higher wages for workers in larger firms remains unexplained. I have explained several other theories in chapter (2). Further empirical studies are needed to discriminate between these explanations.

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Appendix

1. Deriving the Shirking model (Shapiro and Stiglitz, 1984)

Solving (1) with respect to V_e^n

$$V_e^n = w - e + \frac{b}{1+r}V_u + \frac{(1-b)}{1+r}V_e^n$$
(5)

$$\left(1 - \frac{(1-b)}{1+r}\right)V_e^n = w - e + \frac{b}{1+r}V_u$$

 \Leftrightarrow

Both sides multiplied with (1 + r):

$$V_e^n (1 + r - (1 - b)) = (w - e)(1 + r) + bV_u$$
$$\Leftrightarrow$$
$$V_e^n (r + b) = (w - e)(1 + r) + bV_u$$

Divide both sides with (r + b):

$$V_e^n = \frac{(w-e)(1+r) + bV_u}{r+b}$$
(6)

Then I solve equation (3) for V_e^n :

$$V_{e}^{s} = w + \frac{b+q}{1+r}V_{u} + \frac{(1-b-q)}{1+r}V_{e}^{s}$$

$$\Leftrightarrow$$

$$V_{e}^{s}\left(1 - \frac{(1-b-q)}{1+r}\right) = w + \frac{b+q}{1+r}V_{u}$$
(7)

Both sides multiplied with (1 + r)

$$V_e^s = (1 + r - (1 - b - q)) = w(1 + r) + (b + q)V_u$$

$$V_e^s = (r + b + q) = w(1 + r) + (b + q)V_u$$

Divide both sides with (r + b + q):

$$V_e^s = \frac{w(1+r) + (b+q)V_u}{r+b+q}$$
(8)

Solving for (*w*):

$$\frac{(e-w)(1+r) + bV_u}{r+b} \ge \frac{w(1+r) + (b+q)V_u}{r+b+q}$$

Both sides multiplied with (r + b)(r + b + q):

$$[(w - e)(1 + r) + bV_u](r + b + q) \ge [w(1 + r) + (b + q)V_u](r + b)$$

$$\Leftrightarrow$$

$$w(1 + r)(r + b + q) - e(1 + r)(r + b + q) + bV_u(r + b + q)$$

$$\ge w(1 + r)(r + b) + (b + q)V_u(r + b)$$

$$\Leftrightarrow$$

$$w(1 + r)(r + b + q) - e(1 + r(r + b + q) + bV_u(r + b + q))$$

 $-[w(1+r)(r+b) + (b+q)V_u(r+b)] \ge 0$

 \Leftrightarrow

 $w(1+r)(r+b+q-r-b) - e(1+r)(r+b+q) + V_u[b(r+b+q)] - V_u(b+q)$ (r+b) \ge 0

$$w(1+r)q - e(1+r)(r+b+q) - V_u qr \ge 0$$
$$\Leftrightarrow$$
$$w(1+r)q \ge V_u qr + e(1+r)(r+b+q)$$

Divide both sides with (1 + r)q:

$$w \ge \frac{V_u qr}{(1+r)q} + \ge \frac{e(1+r)(r+b+q)}{(1+r)q}$$

$$\Leftrightarrow$$

$$w \ge \frac{r}{1+r}V_u + \frac{e(r+b+q)}{q} = \widehat{w}$$
⁽⁹⁾

2. Variable description: Jobtype and Jobsector

jobtype_i- dummy variable consist 11 occupational classification of survey respondent's job

Table A1.
1. Armed forces
2. Legislators, senior officials and managers
3- Professionals
4. Technicians and associate professionals
5. Clerks
6. Service workers and shop and market sales workers
7. Skilled agricultural and fishery workers
8. Craft and related trades workers
9. Plant and machine operators and assemblers
10. Elementary occupations
11. Unspesified

*jobsector*_i- *dummy variable consist of 22* industry classification of the survey respondent's job

Table A2	
1.Agriculture, forestry and fishing	12. Financial and insurance activities
2.Mining and quarrying	13, Real estate activities
3. Manufacturing	14. Professional, scientific and technical activities
4. Electricity, gas, steam and air conditioning supply	15. Administrative and support service activities
5.Water supply; sewerage, waste management and remediation activities	16. Public administration and defence
6. Construction	17. Education
7. Wholesale and retail trade; repair of motor vehicles and motorcycles	18. Human health and social work activities
8. Transportation and storage	19. Arts, entertainment and recreation
9. Accommodation and food service activities	20. Other service activities
10. Information and communication	21. Activities of extraterritorial organizations and bodies

12.64 (2.9) 13.32 (2.84) 13.67	12.36 (2.43) 12.76	12.36 (2.5)	13.05 (2.69)	13.28	12.72	12.12	12.43	10.95	13.42	14.83
13.32 (2.84)	12.76		(2.69)	(2, 2)						
(2.84)		12.07		(2.2)	(2.56)	(2.43)	(2.87)	(3.5)	(2.45)	(3.15)
		12.87	13.51	13.71	13.41	12.5	13.36	11.77	13.86	15.63
13.67	(2.6)	(2.48)	(2.66)	(2.61)	(2.51)	(2.64)	(2.8)	(3.35)	(2.49)	(2.88)
	12.96	13.09	13.76	13.86	13.8	12.87	13.67	12.01	14.3	16.05
(2.85)	(2.68)	(2.61)	(2.57)	(2.82)	(2.52)	(2.62)	(2.92)	(3.68)	(2.53)	(2.78)
13.93	12.89	13.24	14.08	14.33	13.89	13.02	13.86	12.31	14.33	16.54
(2.87)	(2.72)	(2.87)	(2.52)	(2.98)	(2.79)	(2.69)	(3.09)	(3.21)	(2.7)	(2.69)
14.44	13.29	13.57	14.87	13.95	14.73	13.08	14.06	12.7	14.81	17.2
(2.91)	(2.59)	(2.75)	(2.54)	(2.59)	(2.86)	(2.76)	(3.73)	(3.61)	(2.73)	(2.73)
13.44	12.4	12.98	13.9	13.21	13.29	12.53	13.4	11.82	14.31	15.74
(2.92)	(2.61)	(2.64)	(2.66)	(2.6)	(2.64)	(2.6)	(2.98)	(3.51)	(2.59)	(2.96)
Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.	U.S.
1.29	12.85	12.03	12.91	14.4	12.21	13.34	11.04	12.31	13.19	13.26
3.57)	(2.13)	(3.24)	(2.52)	(2.4)	(2.87)	(2.35)	(3.46)	(2.42)	(2.31)	(3.03)
2.21	13.4	12.79	13.61	14.8	13.19	13.46	12.28	12.89	13.27	14.03
3.68)	(2.38)	(3.17)	(2.53)	(2.08)	(3.02)	(2.53)	(3.77)	(2.19)	(2.34)	(3.)
2.92	13.56	13.84	13.92	15	13.52	13.7	12.84	13.28	13.57	14.39
3.65)	(2.3)	(3.24)	(2.45)	(2.25)	(3.02)	(2.79)	(3.66)	(2.36)	(2.38)	(2.89)
3.06	14.16	13.84	14.19	15.51	13.26	13.56	13.29	13.38	13.71	14.71
3.82)	(2.58)	(3.19)	(2.55)	(2.35)	(2.81)	(2.46)	(3.27)	(2.36)	(2.32)	(2.83)
3.13	14.87	15.19	14.37	15.61	13.54	13.62	13.87	13.67	14.17	15.32
3.61)	(2.31)	(2.88)	(2.67)	(2.39)	(2.81)	(2.41)	(3.47)	(2.61)	(2.24)	(2.76)
			10.55	14.00	12.07	13.52	12.2	12.02	12.55	14.3
2.25	13.54	13.01	13.77	14.98	15.07	13.34	12.2	15.05	15.55	14.5
1.2 3.5 2.2 3.6 2.9 3.6 3.6 3.6 3.8	29 7) 21 88) 22 55) 26 2) 13 31)	29 12.85 7) (2.13) 21 13.4 8) (2.38) 92 13.56 55) (2.3) 06 14.16 22) (2.58) 13 14.87 (1) (2.31)	29 12.85 12.03 7) (2.13) (3.24) 21 13.4 12.79 88) (2.38) (3.17) 92 13.56 13.84 55) (2.3) (3.24) 06 14.16 13.84 22) (2.58) (3.19) 13 14.87 15.19 11) (2.31) (2.88)	29 12.85 12.03 12.91 7) (2.13) (3.24) (2.52) 21 13.4 12.79 13.61 88 (2.38) (3.17) (2.53) 92 13.56 13.84 13.92 55 (2.3) (3.24) (2.45) 96 14.16 13.84 14.19 22 (2.58) (3.19) (2.55) 13 14.87 15.19 14.37 11 (2.31) (2.88) (2.67)	29 12.85 12.03 12.91 14.4 7) (2.13) (3.24) (2.52) (2.4) 21 13.4 12.79 13.61 14.8 88) (2.38) (3.17) (2.53) (2.08) 92 13.56 13.84 13.92 15 55) (2.3) (3.24) (2.45) (2.25) 06 14.16 13.84 14.19 15.51 22 (2.58) (3.19) (2.55) (2.35) 13 14.87 15.19 14.37 15.61 (1) (2.31) (2.88) (2.67) (2.39)	2912.8512.0312.9114.412.21(7)(2.13)(3.24)(2.52)(2.4)(2.87)(2113.412.7913.6114.813.19(8)(2.38)(3.17)(2.53)(2.08)(3.02)(2213.5613.8413.921513.52(5)(2.3)(3.24)(2.45)(2.25)(3.02)(2)(2.58)(3.19)(2.55)(2.35)(2.81)(3)14.8715.1914.3715.6113.54(1)(2.31)(2.88)(2.67)(2.39)(2.81)	2912.8512.0312.9114.412.2113.34 7) (2.13) (3.24) (2.52) (2.4) (2.87) (2.35) 21 13.412.7913.6114.813.1913.46 $88)$ (2.38) (3.17) (2.53) (2.08) (3.02) (2.53) 92 13.5613.8413.921513.5213.7 $55)$ (2.3) (3.24) (2.45) (2.25) (3.02) (2.79) 96 14.1613.8414.1915.5113.2613.56 $2)$ (2.58) (3.19) (2.55) (2.35) (2.81) (2.46) 13 14.8715.1914.3715.6113.5413.62 $11)$ (2.31) (2.88) (2.67) (2.39) (2.81) (2.41)	2912.8512.0312.9114.412.2113.3411.04 7 (2.13) (3.24) (2.52) (2.4) (2.87) (2.35) (3.46) 21 13.412.7913.6114.813.1913.4612.28 $88)$ (2.38) (3.17) (2.53) (2.08) (3.02) (2.53) (3.77) 92 13.5613.8413.921513.5213.712.84 55 (2.3) (3.24) (2.45) (2.25) (3.02) (2.79) (3.66) 96 14.1613.8414.1915.5113.2613.5613.29 22 (2.58) (3.19) (2.55) (2.35) (2.81) (2.46) (3.27) 13 14.8715.1914.3715.6113.5413.6213.87 (1) (2.31) (2.88) (2.67) (2.39) (2.81) (2.41) (3.47)	29 12.85 12.03 12.91 14.4 12.21 13.34 11.04 12.31 $7)$ (2.13) (3.24) (2.52) (2.4) (2.87) (2.35) (3.46) (2.42) 211 13.4 12.79 13.61 14.8 13.19 13.46 12.28 12.89 $8)$ (2.38) (3.17) (2.53) (2.08) (3.02) (2.53) (3.77) (2.19) 92 13.56 13.84 13.92 15 13.52 13.7 12.84 13.28 $5)$ (2.3) (3.24) (2.45) (2.25) (3.02) (2.79) (3.66) (2.36) 66 14.16 13.84 14.19 15.51 13.26 13.56 13.29 13.38 $2)$ (2.58) (3.19) (2.55) (2.35) (2.81) (2.46) (3.27) (2.36) 13 14.87 15.19 14.37 15.61 13.54 13.62 13.87 13.67 $11)$ (2.31) (2.88) (2.67) (2.39) (2.81) (2.41) (3.47) (2.61)	2912.8512.0312.9114.412.2113.3411.0412.3113.19 7) (2.13) (3.24) (2.52) (2.4) (2.87) (2.35) (3.46) (2.42) (2.31) 21 13.412.7913.6114.813.1913.4612.2812.8913.27 $88)$ (2.38) (3.17) (2.53) (2.08) (3.02) (2.53) (3.77) (2.19) (2.34) 92 13.5613.8413.921513.5213.712.8413.2813.57 $55)$ (2.3) (3.24) (2.45) (2.25) (3.02) (2.79) (3.66) (2.36) (2.38) 96 14.1613.8414.1915.5113.2613.5613.2913.3813.71 $22)$ (2.58) (3.19) (2.55) (2.35) (2.81) (2.46) (3.27) (2.36) (2.32) 13 14.8715.1914.3715.6113.5413.6213.8713.6714.17 $11)$ (2.31) (2.88) (2.67) (2.39) (2.81) (2.41) (3.47) (2.61) (2.24)

3. Table (A3) Average formal education

full-time employees aged 35–54. Full-time workers are defined as those working at least 30 h per week

4. Results – full estimation tables

Table A4 Raw data model

	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland	Italy
1.firmsize	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
11to 50	0.117^{***}	0.136***	0.095***	0.101***	0.128^{***}	0.100^{***}	0.064^{**}	0.141^{***}	0.107^{***}	0.149***	0.142^{***}	0.219***
	(0.00)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)
51to 250	0.218***	0.217^{***}	0.187^{***}	0.207^{***}	0.188^{***}	0.185***	0.136***	0.247^{***}	0.163***	0.330***	0.254***	0.313***
	(0.00)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
250to1000	0.321***	0.265^{***}	0.233***	0.360^{***}	0.306***	0.286^{***}	0.223***	0.339***	0.205^{***}	0.468^{***}	0.403***	0.278^{***}
	(0.01)	(0.03)	(0.02)	(0.01)	(0.03)	(0.02)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)
1000 +	0.437***	0.375^{***}	0.293***	0.486^{***}	0.319***	0.336***	0.249***	0.389***	0.353***	0.633***	0.397***	0.401***
	(0.01)	(0.03)	(0.03)	(0.02)	(0.05)	(0.02)	(0.05)	(0.03)	(0.02)	(0.03)	(0.04)	(0.04)
_cons	3.299***	2.377***	2.614***	2.880^{***}	4.550***	5.006***	1.374***	2.628^{***}	2.384^{***}	2.259***	2.610***	2.194***
	(0.00)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Ν	82073	2992	2722	16147	2621	4584	3946	3254	3631	3435	2781	1941
R^2	0.068	0.066	0.068	0.085	0.051	0.070	0.017	0.116	0.065	0.137	0.073	0.100

	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.	USA
1.firmsize	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
11to 50	0.098^{***}	0.130***	0.147^{***}	0.060^{***}	0.190^{***}	0.165***	0.161***	0.074^{***}	0.078^{***}	0.080^{**}
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)	(0.03)
51 to 250	0.259***	0.255***	0.241***	0.183***	0.277***	0.197***	0.319***	0.130***	0.203***	0.234***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.03)
251to 1000	0.413***	0.320***	0.353***	0.253***	0.334***	0.258***	0.356***	0.228***	0.292***	0.411***
	(0.03)	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)
1000+	0.691***	0.574***	0.451***	0.338***	0.398***	0.399***	0.486^{***}	0.224***	0.466***	0.588^{***}
	(0.04)	(0.04)	(0.03)	(0.02)	(0.03)	(0.04)	(0.04)	(0.02)	(0.02)	(0.04)
_cons	7.045***	9.111***	2.518***	5.177***	2.372***	1.144***	1.996***	4.960***	2.180^{***}	2.656***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Ν	3246	3089	3156	3534	3881	2499	2453	2909	4790	2846
R^2	0.123	0.063	0.078	0.095	0.067	0.045	0.101	0.075	0.094	0.103

Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2 . Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001 Full table (A2) is presented in the appendix

Table A5. Model 1 Base Control variables

Table A5. First control variables included. First specification. $jobtype_i$ and $jobsector_i$ is witter here as jobtyp and jobsec

	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland	Italy
.firmsiz	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
									()			()
1, 50	(.) 0.079 ^{****}	(.) 0.099***	(.)	(.) 0.094 ^{***}	(.)	(.) 0.077 ^{***}	(.)	(.) 0.079***	(.) 0.000**	(.)	(.)	(.)
1to 50			0.019		0.090**		0.068**		0.060**	0.060	0.184***	0.094**
	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)
1 to 250	0.129***	0.141***	0.065^{**}	0.155***	0.123***	0.094***	0.112***	0.145***	0.101***	0.185***	0.245^{***}	0.150^{**}
	(0.01)	(0.03)	(0.02)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.05)	(0.04)
51 to	0.200***	0.163***	0.124***	0.244***	0.184***	0.168***	0.193***	0.181***	0.129***	0.248***	0.337***	0.183**
000												
	(0.01)	(0.03)	(0.03)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)	(0.05)	(0.05)
+000 +	0.263***	0.170^{***}	0.129***	0.284***	0.183**	0.190^{***}	0.117^{*}	0.205***	0.233***	0.367***	0.270^{***}	0.258^{**}
	(0.017)	(0.035)	(0.033)	(0.023)	(0.061)	(0.020)	(0.057)	(0.027)	(0.026)	(0.040)	(0.061)	(0.049)
xper	0.017^{***}	0.000	0.013^{*}	0.015^{***}	0.013^{*}	-0.000	0.016^{**}	0.014***	0.021***	0.013^{*}	0.020^{*}	0.014^{**}
	(0.002)	(0.006)	(0.006)	(0.003)	(0.006)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)	(0.008)	(0.005)
xpersq	-0.026***	0.005	-0.023*	-0.025***	-0.020	0.001	-0.032***	-0.025***	-0.031***	-0.012	-0.024	-0.013
	(0.003)	(0.012)	(0.010)	(0.006)	(0.012)	(0.005)	(0.010)	(0.006)	(0.008)	(0.010)	(0.016)	(0.011)
.agecoh	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
.agecoh	-0.001	0.034	0.032	0.015	-0.039	0.004	-0.041	-0.063**	-0.028	0.000	0.020	0.003
	(0.007)	(0.029)	(0.032)	(0.013)	(0.045)	(0.020)	(0.033)	(0.022)	(0.023)	(0.032)	(0.045)	(0.035)
.agecoh	-0.018	(0.02))	0.028	(0.020)	-0.081	0.034	-0.149***	-0.037	-0.052^*	(0.052)	0.041	-0.008
.4500001	(0.018)		(0.028)		(0.046)	(0.034)	(0.037)	(0.024)	(0.024)		(0.041)	(0.036)
agooch	0.012)	0.025	(0.052) 0.081^*	0.004	-0.083	-0.001	(0.037) -0.152***	-0.024)	(0.024) -0.054 [*]	-0.049	-0.031	0.024
.agecoh	(0.020)	(0.025)	(0.081)			(0.022)					(0.031)	(0.024)
0.055-1	· /	· · · ·		(0.020)	(0.051)	· · · ·	(0.040)	(0.026)	(0.027)	(0.036)	· /	
.agecoh	0.032^{*}	0.056	0.100^{*}	-0.001	-0.091	0.004	-0.172^{***}	-0.044	-0.017	-0.078	-0.081	-0.032
	(0.013)	(0.037)	(0.044)	(0.021)	(0.056)	(0.023)	(0.045)	(0.028)	(0.030)	(0.041)	(0.059)	(0.045)
emale	-0.164***	-0.166***	-0.076***	-0.177***	-0.185***	-0.091***	-0.309***	-0.136***	-0.062***	-0.126***	-0.122***	-0.103*
	(0.018)	(0.022)	(0.017)	(0.013)	(0.028)	(0.012)	(0.022)	(0.013)	(0.014)	(0.023)	(0.030)	(0.025)
nigrant	-0.068***	-0.119***	-0.050	-0.046**	-0.016	-0.081***	-0.123***	-0.068^{*}	-0.017	-0.059	-0.045	-0.059
	(0.012)	(0.025)	(0.036)	(0.015)	(0.052)	(0.016)	(0.025)	(0.034)	(0.022)	(0.031)	(0.037)	(0.048)
l.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
.jobtyp	-0.069**	0.005	-0.039	-0.015	-0.066	-0.115***	-0.127***	-0.080**	-0.094**	-0.050	0.097	-0.094
	(0.019)	(0.041)	(0.034)	(0.022)	(0.066)	(0.022)	(0.037)	(0.027)	(0.029)	(0.035)	(0.065)	(0.116)
l.jobtyp	-0.252***	-0.192***	-0.154 ***	-0.222***	-0.202***	-0.202***	-0.336***	-0.312***	-0.325***	-0.330****	-0.117	-0.394
	(0.015)	(0.040)	(0.034)	(0.022)	(0.058)	(0.023)	(0.041)	(0.027)	(0.024)	(0.036)	(0.070)	(0.113)
.jobtyp	-0.389 ****	-0.381****	-0.268 ***	-0.395 ***	-0.305 ^{***}	-0.268 ***	-0.499 ***	-0.456 ***	-0.448 ***	-0.391 ****	-0.290 ****	-0.548
J	(0.021)	(0.044)	(0.035)	(0.025)	(0.063)	(0.027)	(0.049)	(0.030)	(0.028)	(0.040)	(0.077)	(0.115)
ó.jobtyp	-0.513***	-0.464***	-0.337***	-0.480***	-0.450***	-0.393***	-0.757***	-0.526***	-0.528***	-0.565***	-0.434***	-0.569*
Jootjp	(0.024)	(0.047)	(0.039)	(0.025)	(0.067)	(0.026)	(0.040)	(0.030)	(0.030)	(0.046)	(0.074)	(0.115)
.jobtyp	-0.506***	-0.314	-0.771**	-0.409***	-0.923***	-0.374***	-0.567***	-0.672***	-0.670***	-0.581***	-0.424**	-0.649*
Jobtyp	(0.036)	(0.163)	(0.254)	(0.075)	(0.132)	(0.045)	(0.093)	(0.082)	(0.060)	(0.134)	(0.161)	(0.154)
.jobtyp	-0.441***	-0.446^{***}	-0.357***	-0.294***	-0.423***	-0.355***	-0.468***	-0.526***	-0.493***	-0.559***	-0.252^{**}	-0.601^{*}
Jobtyp												
	(0.031)	(0.042)	(0.036)	(0.030)	(0.069)	(0.026)	(0.048)	(0.031)	(0.030)	(0.041)	(0.082)	(0.117)
.jobtyp	-0.543***	-0.522^{***}	-0.468***	-0.455***	-0.481***	-0.465***	-0.582***	-0.555***	-0.588***	-0.661***	-0.456***	-0.646*
0.1.	(0.021)	(0.045)	(0.040)	(0.032)	(0.063)	(0.030)	(0.044)	(0.034)	(0.028)	(0.040)	(0.091)	(0.118)
0.jobty	-0.655***	-0.633***	-0.548***	-0.632***	-0.630***	-0.449***	-0.828***	-0.659 ***	-0.575***	-0.814***	-0.415***	-0.679*
)	(0.000)	(0.04=)	(0.0.10)	(0.000)	(0.0.55)	(0.005	(0.045)	(0.00.1	(0.000)	(0.055)	(0.076)	(0.1.1.1)
	(0.028)	(0.045)	(0.042)	(0.028)	(0.063)	(0.027)	(0.045)	(0.034)	(0.030)	(0.053)	(0.079)	(0.114)
.jobsec	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
.jobsec	0.358***	0.073	0.463	0.456***	0.300**	0.140	0.321**	0.065	-0.165	0.429**	0.532^{**}	0.342
	(0.040)	(0.188)	(0.277)	(0.059)	(0.114)	(0.088)	(0.106)	(0.099)	(0.116)	(0.142)	(0.191)	(0.191)
.jobsec	0.115^{**}	0.246	0.344	0.133**	0.111	0.036	-0.009	0.020	-0.011	0.481***	0.372^{**}	0.241**
	(0.033)	(0.166)	(0.231)	(0.041)	(0.090)	(0.052)	(0.068)	(0.074)	(0.061)	(0.102)	(0.122)	(0.067)
0.jobse	0.292***	0.441^{**}	0.167	0.530***	0.218	0.060	0.077	0.151	0.105	0.491***	0.464**	0.283**
5												
	(0.054)	(0.171)	(0.258)	(0.067)	(0.123)	(0.067)	(0.091)	(0.092)	(0.087)	(0.123)	(0.170)	(0.086)
1.jobse	0.129***	0.051	0.383	0.173	-0.042	-0.010	0.167	-0.047	0.017	0.463***	0.333*	0.244**
	-		-	-						-	-	
	(0.032)	(0.182)	(0.237)	(0.092)	(0.103)	(0.070)	(0.104)	(0.082)	(0.088)	(0.127)	(0.140)	(0.086)
2.jobse	0.171***	0.277	0.254	0.243***	0.163	0.037	0.257**	0.097	-0.048	0.384***	0.381**	0.125
2.j00se	0.1/1	0.277	0.234	0.273	0.105	0.037	0.237	0.077	-0.0+0	0.304	0.501	0.123
	(0.029)	(0.169)	(0.222)	(0.049)	(0.000)	(0.054)	(0.070)	(0.079)	(0.062)	(0, 106)	(0, 1.41)	(0.004)
2:01-	(0.028)	(0.168)	(0.233)	(0.048)	(0.098)	(0.054)	(0.079)	(0.078)	(0.063)	(0.106) 0.225**	(0.141)	(0.084)
3.jobse	0.039	0.176	0.304	0.005	-0.002	-0.018	0.043	0.044	-0.070	0.325**	0.349**	0.169^{*}
	(0.0	(0.4		(0.0.1.1)	(0.0)	(0, 0,)	(0.055)	(0.0==)	(0.0	(0.46.5	(0.465)	(0.5.5.
	(0.031)	(0.166)	(0.231)	(0.041)	(0.092)	(0.055)	(0.072)	(0.075)	(0.062)	(0.104)	(0.123)	(0.066)
4.jobse	0.129***	0.190	0.329	0.139**	0.214*	-0.044	0.138	0.013	0.009	0.284^{**}	0.459**	0.201^{*}

15.jobse	(0.025)	(0.169)	(0.233)	(0.046)	(0.101)	(0.058)	(0.075)	(0.078)	(0.065)	(0.108)	(0.142)	(0.081)
	-0.095*	0.030	0.277	-0.139**	-0.092	-0.042	-0.027	-0.017	-0.127	0.041	0.190	0.137
c	(0.040)	(0.171)	(0.238)	(0.047)	(0.103)	(0.060)	(0.097)	(0.078)	(0.072)	(0.145)	(0.131)	(0.093)
16.jobse	0.220***	0.415 [*]	0.389	0.242***	0.252*	0.062	0.251**	0.059	0.063	0.473 ^{***}	0.402**	0.246*
c	(0.029)	(0.169)	(0.235)	(0.049)	(0.107)	(0.058)	(0.094)	(0.078)	(0.071)	(0.112)	(0.132)	(0.101)
17.jobse	0.285***	0.483**	0.477*	0.271 ^{***}	0.256 [*]	0.171 ^{**}	0.262**	0.140	0.112	0.533 ^{***}	0.671***	0.523***
c	(0.033)	(0.168)	(0.232)	(0.043)	(0.127)	(0.056)	(0.090)	(0.077)	(0.067)	(0.113)	(0.127)	(0.095)
18.jobse	0.136**	0.405*	0.517*	0.092	0.177	0.052	-0.082	-0.058	-0.075	0.346 ^{**}	0.744**	0.207
c	(0.048)	(0.206)	(0.232)	(0.071)	(0.172)	(0.061)	(0.111)	(0.119)	(0.084)	(0.132)	(0.233)	$(0.109) \\ 0.195^{*}$
19.jobse	0.212***	0.185	0.371	0.266***	0.113	0.103	0.089	-0.001	0.025	0.372***	0.662 ^{***}	
c	(0.033)	(0.175)	(0.233)	(0.046)	(0.107)	(0.054)	(0.094)	(0.075)	(0.068)	(0.111)	(0.126)	(0.087)
20.jobse	0.016	0.019	0.342	0.075	-0.019	-0.040	0.052	-0.037	-0.122	0.275*	0.322*	0.068
c	(0.025)	(0.176)	(0.234)	(0.051)	(0.143)	(0.060)	(0.096)	(0.074)	(0.067)	(0.107)	(0.132)	(0.084)
21.jobse	0.210***	0.207	0.382	0.379***	0.132	-0.047	0.144*	-0.052	-0.076	0.451***	0.501***	0.267**
c	(0.050)	(0.165)	(0.231)	(0.041)	(0.091)	(0.054)	(0.073)	(0.075)	(0.060)	(0.107)	(0.128)	(0.070)
22.jobse	0.074	0.146	0.255	0.256***	-0.015	-0.121*	-0.191**	-0.084	-0.139*	0.419***	0.606***	0.073
c	(0.060)	(0.167)	(0.232)	(0.042)	(0.096)	(0.053)	(0.070)	(0.074)	(0.062)	(0.107)	(0.124)	(0.069)
23.jobse	0.090*	0.198	0.305	0.195***	-0.070	-0.127*	0.054	-0.070	-0.130*	0.314 ^{**}	0.370**	0.231**
c	(0.034)	(0.167)	(0.231)	(0.041)	(0.115)	(0.053)	(0.073)	(0.074)	(0.062)	(0.106)	(0.123)	(0.071)
24.jobse	0.011	0.103	0.379	0.186 ^{***}	-0.230	-0.124*	-0.237**	-0.194*	-0.066	0.245	0.507***	0.231*
c	(0.051)	(0.168)	(0.246)	(0.055)	(0.164)	(0.060)	(0.086)	(0.080)	(0.134)	(0.127)	(0.150)	(0.090)
25.jobse	0.053	0.240	0.183	0.131 [*]	-0.036	-0.080	0.007	-0.084	-0.078	0.279*	0.429**	-0.045
c 26.jobse	(0.029) -0.081	(0.169)	(0.240) 0.152	(0.060) 0.160	(0.111)	(0.062)	(0.131)	(0.080) -0.171	(0.081) -0.335	(0.136) 1.190***	(0.149)	(0.135) -0.090
c 27.jobse	(0.050) 0.247	0.803**	(0.284)	(0.141)		-0.278***		(0.122) 0.563***	(0.245) -0.023	(0.108) 1.005***		(0.092)
c _cons	(0.175) 3.568*** (0.057)	(0.308) 2.624 ^{***} (0.175)	2.493*** (0.240)	3.005**** (0.056)	4.832*** (0.118)	(0.070) 5.453*** (0.067)	1.880 ^{***} (0.096)	(0.076) 3.063*** (0.086)	(0.129) 2.658*** (0.077)	(0.108) 2.416 ^{***} (0.129)	2.239*** (0.162)	2.418** (0.136)
$N R^2$	42858	1255	1372	9122	1343	2932	2353	2003	2083	1626	1215	1169
	0.373	0.509	0.367	0.475	0.439	0.407	0.446	0.564	0.468	0.486	0.378	0.429

	Ionon	Varaa	Nothaul	Nomi	Dolond	Clove D	Service	Gruadan	U.K	USA	
	Japan	Korea	Netherl.	Norway	Poland	Slova R.	Spain	Sweden	U.K	USA	
1.firmsiz	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
e											
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	
11to 50	0.070^{*}	0.090^{**}	0.087^{**}	0.058^{**}	0.161***	0.091**	0.030	0.035^{*}	0.143***	0.077	
	(0.032)	(0.032)	(0.026)	(0.021)	(0.035)	(0.033)	(0.029)	(0.014)	(0.035)	(0.041)	
51 to 250	0.137***	0.169***	0.166^{***}	0.125***	0.173***	0.108^{**}	0.149^{***}	0.068^{***}	0.165^{***}	0.160^{***}	
	(0.033)	(0.036)	(0.026)	(0.022)	(0.035)	(0.034)	(0.032)	(0.015)	(0.036)	(0.042)	
251 to	0.245***	0.245***	0.199***	0.131***	0.225***	0.151***	0.190^{***}	0.130***	0.238***	0.266^{***}	
1000											
	(0.041)	(0.048)	(0.029)	(0.026)	(0.049)	(0.042)	(0.040)	(0.020)	(0.038)	(0.047)	
1000 +	0.406***	0.476^{***}	0.225***	0.178^{***}	0.322***	0.242^{***}	0.280^{***}	0.127^{***}	0.309^{***}	0.322^{***}	
	(0.043)	(0.054)	(0.037)	(0.027)	(0.055)	(0.052)	(0.043)	(0.020)	(0.039)	(0.051)	
exper	0.033***	0.025***	0.004	0.009^{*}	0.024^{***}	0.010	0.015^{**}	0.009^{**}	0.018^{**}	0.011	
	(0.005)	(0.005)	(0.006)	(0.004)	(0.006)	(0.007)	(0.005)	(0.003)	(0.006)	(0.007)	
expersq	-0.059***	-0.043***	-0.006	-0.018^{*}	-0.039***	-0.020	-0.020	-0.013*	-0.030**	-0.019	
	(0.010)	(0.012)	(0.010)	(0.007)	(0.012)	(0.015)	(0.010)	(0.005)	(0.011)	(0.012)	
1.agecoh	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	
2.agecoh	0.038	-0.023	0.107^{***}	0.000	0.033	-0.041	0.038	0.020	-0.003	0.025	
	(0.033)	(0.035)	(0.031)	(0.022)	(0.046)	(0.040)	(0.036)	(0.020)	(0.039)	(0.039)	
3.agecoh	-0.006	-0.074	0.086^{*}	0.025	-0.067	-0.018	0.046	0.025	-0.018		
	(0.036)	(0.039)	(0.034)	(0.023)	(0.044)	(0.046)	(0.034)	(0.021)	(0.042)		
4.agecoh	0.055	-0.052	0.075*	0.057*	-0.050	-0.016	0.014	0.036	-0.075	0.041	
	(0.044)	(0.039)	(0.034)	(0.025)	(0.049)	(0.049)	(0.035)	(0.022)	(0.044)	(0.041)	
5.agecoh	0.051	-0.100^{*}	0.073	0.039	-0.070	-0.018	-0.026	0.027	-0.072	0.058	

	(0.041)	(0.044)	(0.039)	(0.028)	(0.053)	(0.057)	(0.041)	(0.024)	(0.046)	(0.047)
female	-0.342***	-0.289***	-0.065**	-0.112***	-0.147***	-0.232***	-0.146***	-0.076***	-0.137***	-0.162***
	(0.026)	(0.030)	(0.021)	(0.014)	(0.029)	(0.027)	(0.024)	(0.011)	(0.025)	(0.030)
migrant	0.199^{***}	-0.065	-0.117***	-0.065**	0.000	0.081	-0.072	-0.051***	-0.016	-0.090^{*}
	(0.043)	(0.088)	(0.034)	(0.023)	(.)	(0.089)	(0.048)	(0.014)	(0.033)	(0.039)
2.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
3.jobtyp	-0.175***	-0.168*	-0.046	-0.016	-0.185**	-0.122	-0.122	-0.126***	-0.046	0.016
4 * 1 4	(0.044)	(0.067)	(0.029)	(0.023)	(0.060)	(0.064)	(0.076)	(0.022)	(0.042)	(0.044)
4.jobtyp	-0.289***	-0.496***	-0.183***	-0.118***	-0.362***	-0.316***	-0.442***	-0.248***	-0.110^{*}	-0.276*** (0.047)
5.jobtyp	(0.040) -0.419***	(0.071) -0.367***	(0.030) -0.372***	(0.024) -0.294***	(0.059) -0.633****	(0.061) -0.455***	(0.083) -0.492***	(0.023) -0.395***	(0.043) -0.409***	(0.047) -0.565***
5.j00typ	(0.043)	(0.066)	(0.034)	(0.033)	(0.068)	(0.069)	(0.081)	(0.029)	(0.046)	(0.049)
6.jobtyp	-0.520***	-0.708***	-0.395***	-0.298***	-0.757***	-0.703^{***}	-0.652^{***}	-0.366***	-0.496***	-0.632***
0.j00t/jp	(0.047)	(0.070)	(0.037)	(0.028)	(0.064)	(0.065)	(0.080)	(0.023)	(0.043)	(0.052)
7.jobtyp	-0.471***	-0.414*	-0.773***	-0.650	-0.793***	-0.622***	-0.659***	-0.485***	-0.544**	-0.415
5 51	(0.124)	(0.193)	(0.113)	(0.357)	(0.145)	(0.094)	(0.097)	(0.064)	(0.174)	(0.350)
8.jobtyp	-0.563***	-0.601***	-0.412***	-0.298***	-0.712***	-0.577***	-0.588***	-0.400****	-0.375***	-0.499***
	(0.046)	(0.068)	(0.036)	(0.030)	(0.061)	(0.068)	(0.087)	(0.028)	(0.050)	(0.057)
9.jobtyp	-0.622***	-0.737***	-0.544***	-0.350***	-0.706***	-0.655***	-0.657***	-0.433***	-0.549***	-0.749***
	(0.050)	(0.071)	(0.053)	(0.037)	(0.066)	(0.064)	(0.089)	(0.030)	(0.045)	(0.053)
10.jobtyp	-0.608***	-0.818***	-0.569***	-0.370***	-0.756***	-0.776***	-0.761***	-0.532***	-0.686***	-0.747***
	(0.086)	(0.068)	(0.047)	(0.044)	(0.060)	(0.066)	(0.082)	(0.031)	(0.045)	(0.091)
7.jobsec	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.1	(.)	(.)	(.) 0.471***	(.)	(.) 0.050*	(.)	(.)	(.) 0.289***	(.)	(.)
8.jobsec	0.223	0.246	0.471***	0.370***	0.252^{*}	0.115	0.379*		0.372	0.602^{**}
9.jobsec	(0.127) 0.245*	(0.134) -0.077	(0.095) 0.078	(0.049) 0.062^*	(0.118) -0.053	(0.125) 0.105	(0.158) 0.229***	(0.080) 0.021	(0.280) 0.075	(0.227) 0.142
9.100800	(0.118)	(0.121)	(0.078)	(0.028)	-0.033 (0.088)	(0.064)	(0.229)	(0.021)	(0.205)	(0.142)
10.jobsec	0.481**	0.186	0.236	0.136*	-0.005	0.259**	0.670***	0.119	-0.064	0.361*
10.j00500	(0.179)	(0.196)	(0.121)	(0.056)	(0.095)	(0.090)	(0.176)	(0.061)	(0.222)	(0.166)
11.jobsec	0.293	0.107	0.136	0.057	-0.152	0.137	0.255**	0.153	0.019	0.070
J	(0.150)	(0.172)	(0.127)	(0.161)	(0.119)	(0.085)	(0.089)	(0.079)	(0.214)	(0.188)
12.jobsec	0.222	-0.034	0.068	0.046	-0.026	0.139	0.185***	0.127*	0.202	0.289
	(0.124)	(0.124)	(0.089)	(0.027)	(0.091)	(0.077)	(0.054)	(0.052)	(0.210)	(0.157)
13.jobsec	0.151	-0.030	0.058	0.015	-0.109	0.135	0.130^{*}	0.037	-0.090	0.038
	(0.121)	(0.122)	(0.089)	(0.027)	(0.092)	(0.070)	(0.054)	(0.051)	(0.205)	(0.152)
14.jobsec	0.208	-0.008	0.051	-0.009	-0.016	0.215**	0.242***	0.043	0.115	0.285
	(0.124)	(0.131)	(0.098)	(0.037)	(0.098)	(0.071)	(0.065)	(0.054)	(0.205)	(0.163)
15.jobsec	0.103	-0.159	-0.155	-0.086	-0.057	0.052	0.190***	-0.044	-0.088	-0.172
16 johaaa	(0.163)	(0.122) 0.197	(0.112) 0.227^*	(0.095) 0.177 ^{****}	(0.115) 0.182	(0.079) 0.614^{***}	(0.057) 0.327***	(0.064) 0.117^*	(0.214) 0.234	(0.155) 0.372 [*]
16.jobsec	0.288 [*] (0.127)	(0.197	(0.095)	(0.036)	(0.182)	(0.133)	(0.090)	(0.054)	(0.234 (0.212)	(0.156)
17.jobsec	0.517***	0.310*	0.266**	0.115*	0.211	0.320**	0.479***	0.156**	0.349	0.288
17.500300	(0.143)	(0.138)	(0.092)	(0.046)	(0.159)	(0.112)	(0.092)	(0.057)	(0.215)	(0.156)
18.jobsec	0.185	-0.160	0.318***	0.005	-0.019	-0.029	0.321	0.059	-0.021	0.483**
5	(0.138)	(0.167)	(0.095)	(0.090)	(0.117)	(0.123)	(0.241)	(0.060)	(0.238)	(0.185)
19.jobsec	0.323*	0.218	0.241**	0.155***	0.056	0.070	0.222**	0.136**	0.259	0.372*
	(0.128)	(0.137)	(0.091)	(0.036)	(0.115)	(0.094)	(0.079)	(0.051)	(0.209)	(0.158)
20.jobsec	0.105	-0.199	0.036	0.026	-0.285*	0.101	0.149^{*}	-0.018	-0.122	0.012
	(0.126)	(0.125)	(0.096)	(0.048)	(0.118)	(0.089)	(0.059)	(0.051)	(0.210)	(0.163)
21.jobsec	0.408***	0.201	0.163	-0.011	0.126	0.226**	0.411***	-0.017	0.177	0.254
22 J-L	(0.123) 0.395**	(0.130)	(0.087)	(0.030) -0.135***	(0.092)	(0.074)	(0.052) 0.306***	(0.052) -0.168***	(0.207)	(0.155)
22.jobsec		0.113	0.034		-0.068	-0.041			0.028	-0.075
23.jobsec	(0.128) 0.240^*	(0.129) -0.115	(0.089) 0.100	(0.027) -0.044	(0.087) -0.193*	(0.071) 0.036	(0.058) 0.255***	(0.050) -0.035	(0.208) 0.037	(0.153) 0.106
23.J00sec	(0.121)	(0.125)	(0.088)	(0.026)	(0.091)	(0.073)	(0.060)	(0.050)	(0.206)	(0.152)
24.jobsec	0.158	-0.066	0.112	0.023	-0.088	0.139	0.159	-0.103	-0.142	0.081
	(0.138)	(0.191)	(0.112)	(0.064)	(0.113)	(0.122)	(0.151)	(0.066)	(0.224)	(0.173)
25.jobsec	0.061	-0.146	0.159	0.057	-0.341	0.102	0.024	-0.015	-0.048	0.115
5	(0.128)	(0.135)	(0.105)	(0.047)	(0.201)	(0.153)	(0.076)	(0.074)	(0.220)	(0.162)
26.jobsec	. ,	-0.428**	. ,	. ,	. ,	. ,	-0.055	. ,	0.347	0.148
-		(0.145)					(0.084)		(0.234)	(0.184)
27.jobsec									0.256	
									(0.208)	
_cons	7.106***	9.593***	2.792***	5.390***	2.878^{***}	1.602***	2.247***	5.211***	2.414***	2.984***
	(0.136)	(0.137)	(0.113)	(0.061)	(0.115)	(0.115)	(0.101)	(0.065)	(0.217)	(0.178)
$N_{\mathbf{p}^2}$	1747	1717	1328	1579	1002	1511	1396	1798	2106	1506
R^2	0.481	0.513	0.448	0.449	0.487	0.377	0.491	0.495	0.483	0.467

Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Sample: full-time employees aged 35–54. Numeracy score standardized to std. dev. 1 within each country. Experiencesq divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R² refers to within-country R². Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001 Full table (C) is presented in the appendix

 Table A6. Model 2 Controlling for formal education

Table A6 Including education

14010 110 1	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland	Italy
1.firmsiz	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
e	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
11to 50	0.069***	0.104***	0.010	0.087***	0.085**	0.070***	0.065*	0.074***	0.047**	0.051	0.169***	0.075*
	(0.005)	(0.025)	(0.024)	(0.018)	(0.029)	(0.015)	(0.025)	(0.015)	(0.018)	(0.035)	(0.042)	(0.031)
51 to 250	0.112 ^{***} (0.006)	0.140 ^{***} (0.026)	0.056 [*] (0.024)	0.145 ^{***} (0.018)	0.110 ^{**} (0.035)	0.078 ^{***} (0.015)	0.102*** (0.027)	0.138 ^{****} (0.016)	0.092 ^{***} (0.019)	0.162*** (0.035)	0.213*** (0.045)	0.127 ^{***} (0.035)
251 to 1000	0.176***	0.167***	0.110***	0.221***	0.171***	0.157***	0.167***	0.172***	0.109***	0.233***	0.287***	0.161***
	(0.008)	(0.029)	(0.026)	(0.020)	(0.041)	(0.019)	(0.034)	(0.020)	(0.021)	(0.039)	(0.046)	(0.045)
1000 +	0.231^{***}	0.162^{***}	0.112 ^{***} (0.032)	0.246^{***}	0.185^{***}	0.155 ^{***} (0.019)	0.106 (0.054)	0.201^{***}	0.218^{***}	0.344***	0.223^{***}	0.228***
educ	(0.016) 0.036 ^{***}	(0.033) 0.045***	0.032)	(0.022) 0.031***	(0.053) 0.036***	0.034***	0.032***	(0.026) 0.026***	(0.026) 0.026***	(0.041) 0.035***	(0.056) 0.044^{***}	(0.050) 0.025***
	(0.002)	(0.004)	(0.004)	(0.003)	(0.006)	(0.003)	(0.004)	(0.003)	(0.002)	(0.006)	(0.006)	(0.006)
exper	0.017***	0.005	0.013*	0.015***	0.016*	0.004	0.017**	0.015***	0.019***	0.015**	0.018*	0.013**
expersq	(0.002) -0.024***	(0.006) -0.000	(0.005) -0.016	(0.003) -0.021***	(0.006) -0.022	(0.003) -0.001	(0.005) -0.031**	(0.003) -0.022***	(0.004) -0.024**	(0.006) -0.015	(0.008) -0.016	(0.005) -0.006
слрегзч	(0.003)	(0.012)	(0.010)	(0.006)	(0.012)	(0.001)	(0.010)	(0.006)	(0.008)	(0.010)	(0.015)	(0.011)
1.agecoh	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2 agaaah	(.)	(.) 0.034	(.) 0.022	(.) 0.014	(.) -0.047	(.) 0.005	(.) -0.049	(.) -0.060**	(.) -0.008	(.) -0.003	(.) 0.025	(.) 0.009
2.agecoh	-0.002 (0.007)	(0.034)	(0.022)	(0.014)	-0.047 (0.043)	(0.003)	(0.033)	(0.022)	-0.008 (0.022)	(0.003)	(0.023)	(0.009
3.agecoh	-0.017	(01027)	0.014	(0101))	-0.096*	0.031	-0.175***	-0.038	-0.023	(01002)	0.049	-0.006
-	(0.013)	0.000	(0.031)	0.001	(0.047)	(0.019)	(0.036)	(0.024)	(0.023)	0.07:	(0.048)	(0.035)
4.agecoh	-0.021 (0.012)	0.009 (0.030)	0.052 (0.035)	0.001 (0.019)	-0.095 (0.050)	-0.010 (0.021)	-0.184 ^{***} (0.040)	-0.030 (0.026)	-0.032 (0.027)	-0.054 (0.037)	-0.014 (0.056)	0.029 (0.041)
5.agecoh	-0.038^{**}	0.041	0.045	-0.006	(0.030) -0.118 [*]	-0.018	-0.216***	-0.056*	0.008	-0.095*	-0.051	-0.034
U	(0.012)	(0.035)	(0.041)	(0.020)	(0.058)	(0.022)	(0.045)	(0.027)	(0.030)	(0.041)	(0.055)	(0.042)
female	-0.153***	-0.128***	-0.071***	-0.159***	-0.145***	-0.086***	-0.304***	-0.138***	-0.068****	-0.111****	-0.123****	-0.115****
migrant	(0.017) -0.091***	(0.021) -0.141***	(0.016) -0.031	(0.013) -0.072***	(0.028) -0.035	(0.011) -0.090****	(0.021) -0.129***	(0.013) -0.090**	(0.014) -0.000	(0.023) -0.042	(0.029) -0.082*	(0.025) -0.074
mgram	(0.015)	(0.023)	(0.033)	(0.012)	(0.053)	(0.016)	(0.025)	(0.034)	(0.022)	(0.033)	(0.035)	(0.046)
2.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.1.1.	(.)	(.)	(.)	(.)	(.)	(.) -0.114 ^{****}	(.)	(.)	(.)	(.)	(.)	(.)
3.jobtyp	-0.085*** (0.018)	-0.035 (0.038)	-0.035 (0.033)	-0.027 (0.021)	-0.079 (0.064)	(0.021)	-0.139*** (0.036)	-0.076** (0.025)	-0.091*** (0.027)	-0.093** (0.033)	0.063 (0.062)	-0.116 (0.119)
4.jobtyp	-0.212***	-0.129***	-0.119***	-0.191***	-0.152*	-0.165***	-0.295***	-0.260***	-0.262***	-0.262***	-0.125	-0.344**
	(0.014)	(0.037)	(0.034)	(0.022)	(0.060)	(0.023)	(0.040)	(0.025)	(0.024)	(0.037)	(0.067)	(0.116)
5.jobtyp	-0.327^{***}	-0.278*** (0.042)	-0.201^{***}	-0.353***	-0.240^{***}	-0.205^{***}	-0.429***	-0.379***	-0.372^{***}	-0.300^{***}	-0.256^{***}	-0.469^{***}
6.jobtyp	(0.023) -0.422***	-0.357***	(0.035) -0.257***	(0.025) -0.421***	(0.065) -0.347***	(0.026) -0.308***	(0.049) -0.670 ^{***}	(0.028) -0.421***	(0.028) -0.439***	(0.042) -0.461***	(0.073) -0.351***	(0.117) -0.445***
oljootjp	(0.024)	(0.046)	(0.039)	(0.026)	(0.071)	(0.027)	(0.041)	(0.030)	(0.030)	(0.047)	(0.070)	(0.121)
7.jobtyp	-0.399***	-0.239	-0.728**	-0.339***	-0.889***	-0.290***	-0.477***	-0.536***	-0.545***	-0.472***	-0.398*	-0.513***
8.jobtyp	(0.030) -0.341***	(0.161) -0.349***	(0.221) -0.278***	(0.078) -0.232***	(0.132) -0.313***	(0.045) -0.274***	(0.091) -0.365***	(0.077) -0.414***	(0.053) -0.385***	(0.137) -0.444***	(0.157) -0.201*	(0.151) -0.468***
0.J00typ	(0.022)	(0.041)	(0.037)	(0.030)	(0.073)	(0.026)	(0.048)	(0.032)	(0.030)	(0.044)	(0.079)	(0.123)
9.jobtyp	-0.423***	-0.394***	-0.358***	-0.378***	-0.368 ^{****}	-0.348 ***	-0.478***	-0.434***	-0.466***	-0.537***	-0.324***	-0.497***
10 :-1.	(0.017) -0.517***	(0.044) -0.444 ^{***}	(0.042) -0.415***	(0.033) -0.546***	(0.068) -0.499***	(0.031) -0.326***	(0.045) -0.720***	(0.035) -0.531***	(0.029) -0.443***	(0.045) -0.635***	(0.086) -0.304***	(0.124) -0.529***
10.jobty p	-0.517	-0.444	-0.415	-0.340	-0.499	-0.520	-0.720	-0.551	-0.445	-0.055	-0.304	-0.329
r	(0.030)	(0.045)	(0.044)	(0.029)	(0.070)	(0.029)	(0.046)	(0.035)	(0.031)	(0.062)	(0.076)	(0.121)
7.jobsec	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
8.jobsec	(.) 0.338***	(.) 0.037	(.) 0.477	(.) 0.451***	(.) 0.288**	(.) 0.119	(.) 0.312**	(.) 0.082	(.) -0.156	(.) 0.422**	(.) 0.402**	(.) 0.301
0.900.00	(0.040)	(0.188)	(0.246)	(0.058)	(0.107)	(0.094)	(0.106)	(0.090)	(0.103)	(0.145)	(0.154)	(0.187)
9.jobsec	0.100**	0.217	0.360	0.142^{***}	0.106	0.047	-0.026	0.027	-0.004	0.483***	0.256*	0.225***
10.jobse	(0.032) 0.258***	(0.170) 0.365*	(0.209) 0.205	(0.041) 0.528^{***}	(0.092) 0.229	(0.053) 0.072	(0.068) 0.031	(0.070) 0.119	(0.057) 0.090	(0.101) 0.480^{***}	(0.110) 0.409**	(0.067) 0.230**
c	0.230	0.505	0.205	0.520	0.229	0.072	0.031	0.117	0.090	0.400	0.407	0.250
	(0.054)	(0.175)	(0.233)	(0.066)	(0.120)	(0.065)	(0.090)	(0.087)	(0.082)	(0.121)	(0.146)	(0.089)
11.jobsec	0.115**	-0.037	0.385	0.145	-0.009	0.001	0.139	-0.037	0.031	0.453***	0.195	0.224**
12.jobsec	(0.032) 0.163***	(0.179) 0.258	(0.214) 0.275	(0.094) 0.265***	(0.105) 0.161	(0.068) 0.055	(0.100) 0.225 ^{**}	(0.080) 0.108	(0.082) -0.003	(0.126) 0.379***	(0.138) 0.265*	(0.086) 0.122
12.300300	(0.029)	(0.172)	(0.212)	(0.047)	(0.099)	(0.055)	(0.079)	(0.073)	(0.060)	(0.105)	(0.129)	(0.082)
13.jobsec	0.025	0.147	0.307	0.018	-0.022	-0.000	0.015	0.047	-0.057	0.324**	0.267^{*}	0.140^{*}
14:-1	(0.029)	(0.171)	(0.210)	(0.040)	(0.095)	(0.055)	(0.071)	(0.071)	(0.058)	(0.103)	(0.111)	(0.066)
14.jobsec	0.112*** (0.024)	0.166 (0.174)	0.349 (0.211)	0.150 ^{***} (0.045)	0.206^{*} (0.101)	-0.019 (0.059)	0.113 (0.074)	0.019 (0.075)	0.002 (0.062)	0.292 ^{**} (0.107)	0.353** (0.131)	0.188^{*} (0.079)
15.jobsec	(0.024) -0.093*	0.020	0.287	-0.103^{*}	-0.103	-0.047	-0.042	-0.015	-0.102	0.036	0.097	0.118
	(0.036)	(0.175)	(0.215)	(0.047)	(0.107)	(0.061)	(0.096)	(0.075)	(0.069)	(0.142)	(0.115)	(0.094)
16.jobsec	0.192***	0.426^{*}	0.383	0.239***	0.202^{*}	0.072	0.241^{*}	0.075	0.050	0.476***	0.273^{*}	0.226^{*}

	(0.025)	(0.174)	(0.214)	(0.048)	(0.102)	(0.058)	(0.094)	(0.074)	(0.067)	(0.111)	(0.121)	(0.095)
17.jobsec	0.254***	0.469^{**}	0.459^{*}	0.261***	0.191	0.170^{**}	0.214^{*}	0.130	0.099	0.544^{***}	0.537***	0.494^{**}
U U	(0.030)	(0.172)	(0.211)	(0.042)	(0.133)	(0.057)	(0.088)	(0.073)	(0.063)	(0.112)	(0.115)	(0.098)
18.jobsec	0.109^{*}	0.342	0.503^{*}	0.089	0.165	0.045	-0.106	-0.029	-0.080	0.318^{*}	0.692^{***}	0.132
c .	(0.046)	(0.211)	(0.210)	(0.069)	(0.175)	(0.062)	(0.111)	(0.115)	(0.080)	(0.130)	(0.203)	(0.114)
19.jobsec	0.162***	0.133	0.353	0.245***	0.072	0.085	0.035	-0.009	0.005	0.357**	0.521***	0.169*
5	(0.031)	(0.177)	(0.211)	(0.046)	(0.109)	(0.055)	(0.093)	(0.071)	(0.064)	(0.110)	(0.117)	(0.084
20.jobsec	0.001	0.010	0.356	0.073	-0.034	-0.013	0.013	-0.041	-0.100	0.274*	0.254*	0.034
5	(0.024)	(0.179)	(0.212)	(0.052)	(0.144)	(0.060)	(0.097)	(0.071)	(0.062)	(0.107)	(0.120)	(0.081
21.jobsec	0.170**	0.170	0.378	0.358***	0.079	-0.058	0.097	-0.053	-0.073	0.431***	0.372**	0.212*
5	(0.050)	(0.169)	(0.209)	(0.041)	(0.094)	(0.054)	(0.072)	(0.072)	(0.057)	(0.106)	(0.117)	(0.071
22.jobsec	0.016	0.080	0.233	0.210***	-0.062	-0.134*	-0.227**	-0.108	-0.152**	0.403***	0.417***	0.044
5	(0.056)	(0.171)	(0.210)	(0.041)	(0.098)	(0.054)	(0.070)	(0.071)	(0.059)	(0.105)	(0.112)	(0.069
23.jobsec	0.060	0.125	0.301	0.184***	-0.075	-0.124*	0.024	-0.086	-0.123*	0.295**	0.245*	0.217*
5	(0.033)	(0.172)	(0.209)	(0.040)	(0.116)	(0.054)	(0.072)	(0.070)	(0.058)	(0.104)	(0.111)	(0.074
24.jobsec	-0.018	0.051	0.370	0.149**	-0.263	-0.096	-0.258**	-0.178*	-0.070	0.263*	0.410**	0.183*
5	(0.048)	(0.171)	(0.227)	(0.052)	(0.165)	(0.061)	(0.085)	(0.076)	(0.130)	(0.120)	(0.149)	(0.092
25.jobsec	0.018	0.192	0.202	0.118*	-0.072	-0.094	-0.041	-0.086	-0.067	0.258	0.316*	-0.063
5	(0.027)	(0.173)	(0.219)	(0.060)	(0.108)	(0.062)	(0.127)	(0.076)	(0.075)	(0.133)	(0.133)	(0.125)
26.jobsec	-0.082		0.179	0.123				-0.186	0.056	1.199***		-0.102
5	(0.050)		(0.253)	(0.135)				(0.127)	(0.106)	(0.107)		(0.093
27.jobsec	0.190	0.656^{*}				-0.282**		0.563***	-0.079	0.875***		
U U	(0.159)	(0.294)				(0.092)		(0.072)	(0.120)	(0.107)		
_cons	3.041***	1.940^{***}	1.975^{***}	2.539***	4.240^{***}	4.884^{***}	1.449^{***}	2.627***	2.263***	1.834***	1.679^{***}	2.060^{**}
	(0.067)	(0.189)	(0.225)	(0.070)	(0.153)	(0.079)	(0.113)	(0.093)	(0.080)	(0.163)	(0.167)	(0.169)
Ν	42424	1255	1371	9080	1342	2932	2353	2003	2076	1607	1215	1169
R^2	0.401	0.556	0.404	0.493	0.464	0.456	0.460	0.588	0.502	0.502	0.415	0.451

	Japan	Korea	Netherl.	Norway	Poland	Slova R.	Spain	Sweden	U.K	USA
1.firmsiz	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
e										
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
11to 50	0.061^{*}	0.076^{*}	0.075^{**}	0.052^{*}	0.151***	0.082^{*}	0.034	0.029^{*}	0.157***	0.087^{*}
	(0.031)	(0.031)	(0.026)	(0.021)	(0.035)	(0.032)	(0.027)	(0.014)	(0.038)	(0.043)
51 to 250	0.128***	0.125***	0.141***	0.110***	0.141***	0.079^{*}	0.142***	0.056***	0.173***	0.168^{***}
	(0.032)	(0.035)	(0.025)	(0.022)	(0.035)	(0.033)	(0.030)	(0.015)	(0.038)	(0.042)
251to	0.230***	0.187^{***}	0.174***	0.109***	0.206***	0.133**	0.161***	0.121***	0.242***	0.257***
1000										
	(0.039)	(0.046)	(0.028)	(0.026)	(0.047)	(0.042)	(0.037)	(0.020)	(0.041)	(0.049)
1000 +	0.372***	0.405^{***}	0.195***	0.158^{***}	0.287^{***}	0.211***	0.253***	0.115***	0.301***	0.331***
	(0.042)	(0.051)	(0.036)	(0.026)	(0.054)	(0.051)	(0.042)	(0.020)	(0.041)	(0.051)
educ	0.037***	0.039***	0.045***	0.033***	0.052^{***}	0.054^{***}	0.040^{***}	0.021***	0.036***	0.054^{***}
	(0.005)	(0.005)	(0.004)	(0.003)	(0.007)	(0.006)	(0.004)	(0.003)	(0.005)	(0.006)
exper	0.034***	0.025***	0.005	0.010^{*}	0.020^{***}	0.013	0.014^{**}	0.010^{**}	0.022^{***}	0.011
	(0.005)	(0.005)	(0.005)	(0.004)	(0.006)	(0.008)	(0.005)	(0.003)	(0.006)	(0.007)
expersq	-0.056***	-0.038**	0.002	-0.015*	-0.026*	-0.019	-0.014	-0.012^{*}	-0.036**	-0.017
	(0.010)	(0.012)	(0.009)	(0.008)	(0.011)	(0.015)	(0.010)	(0.005)	(0.011)	(0.012)
1.agecoh	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2.agecoh	0.033	-0.022	0.087^{**}	-0.004	0.033	-0.034	0.030	0.012	-0.005	0.025
	(0.033)	(0.033)	(0.030)	(0.021)	(0.044)	(0.039)	(0.034)	(0.020)	(0.039)	(0.040)
3.agecoh	-0.012	-0.065	0.088^{**}	0.016	-0.049	-0.022	0.046	0.012	-0.031	
	(0.035)	(0.039)	(0.031)	(0.023)	(0.042)	(0.046)	(0.034)	(0.021)	(0.042)	
4.agecoh	0.037	-0.034	0.061	0.045	-0.039	-0.040	0.013	0.016	-0.079	0.023
	(0.042)	(0.039)	(0.033)	(0.025)	(0.047)	(0.049)	(0.034)	(0.022)	(0.043)	(0.042)
5.agecoh	0.013	-0.047	0.038	0.018	-0.064	-0.053	-0.017	-0.001	-0.070	0.044
	(0.040)	(0.044)	(0.036)	(0.028)	(0.050)	(0.057)	(0.039)	(0.024)	(0.047)	(0.048)
female	-0.308****	-0.248***	-0.050*	-0.106***	-0.137***	-0.202***	-0.140***	-0.077***	-0.136***	-0.128***
	(0.027)	(0.030)	(0.021)	(0.013)	(0.028)	(0.026)	(0.023)	(0.011)	(0.025)	(0.032)
migrant	0.319***	-0.055	-0.114***	-0.084***	0.000	0.043	-0.078	-0.047**	-0.038	-0.069
0.1.1	(0.046)	(0.085)	(0.033)	(0.023)	(.)	(0.095)	(0.048)	(0.014)	(0.034)	(0.039)
2.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2:-1.	(.)	(.) 0 177**	(.)	(.)	(.)	(.)	(.)	(.) -0.142***	(.)	(.)
3.jobtyp	-0.191***	-0.177**	-0.073**	-0.041	-0.191***	-0.099	-0.114		-0.076	-0.044
1 inktore	(0.043) -0.264***	(0.063) -0.423***	(0.026) -0.153***	(0.022) -0.108***	(0.055) -0.306***	(0.062) -0.197**	(0.073) -0.347***	(0.020) -0.231***	(0.042) -0.108*	(0.042) -0.202***
4.jobtyp							-0.347 (0.078)			
5 ichtru	(0.039) -0.378***	(0.068) -0.309***	(0.028) -0.308***	(0.024) -0.224***	(0.056) -0.518***	(0.061) -0.311***	(0.078) -0.380***	(0.023) -0.359***	(0.043) -0.375***	(0.048) -0.474***
5.jobtyp										
6 johtur	(0.043) -0.465***	(0.062) -0.595***	(0.034) -0.306***	(0.033) -0.238***	(0.065) -0.585***	(0.070) -0.508***	(0.078) -0.471***	(0.029) -0.318***	(0.046) -0.415***	(0.057) -0.525***
6.jobtyp		-0.395 (0.067)	-0.306 (0.037)	-0.238 (0.028)	-0.585 (0.063)		(0.078)	(0.025)	(0.0415)	-0.525 (0.055)
7.jobtyp	(0.046) -0.382**	-0.272	(0.037) -0.634 ^{***}	-0.550	(0.063) -0.500 ^{**}	(0.068) -0.395***	(0.078) -0.470***	(0.025) -0.430***	(0.045) -0.459 [*]	-0.184
,.jooryp	-0.362	-0.272	-0.054	-0.550	-0.500	-0.375	-0.470	-0.450	-0.437	-0.104

	(0.116)	(0.187)	(0.106)	(0.381)	(0.152)	(0.093)	(0.099)	(0.061)	(0.202)	(0.278)
8.jobtyp	-0.470^{***}	-0.460***	-0.326***	-0.253***	-0.508***	-0.361***	-0.384***	-0.366***	-0.320***	-0.358***
8.j00typ	(0.047)	-0.400	(0.035)	(0.030)	(0.062)	(0.072)	(0.084)	(0.028)	(0.051)	(0.063)
9.jobtyp	-0.522***	-0.582***	-0.402***	-0.284***	-0.478***	-0.434***	-0.427***	-0.393***	-0.502***	-0.565***
JJOOtyp	(0.052)	(0.071)	(0.051)	(0.038)	(0.069)	(0.069)	(0.088)	(0.031)	(0.051)	(0.061)
10.jobtyp	-0.508***	-0.642***	-0.445***	-0.289***	-0.516***	-0.508***	-0.551***	-0.463^{***}	-0.648***	-0.547***
10.j00typ	(0.086)	(0.066)	(0.047)	(0.048)	(0.064)	(0.072)	(0.082)	(0.034)	(0.050)	(0.095)
7.jobsec	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
7.300500	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
8.jobsec	0.304*	0.129	0.421***	0.400***	0.236*	0.123	0.264	0.343***	0.204	0.721***
0.900000	(0.125)	(0.126)	(0.093)	(0.050)	(0.107)	(0.123)	(0.159)	(0.076)	(0.368)	(0.216)
9.jobsec	0.219	-0.149	0.093	0.117***	-0.065	0.097	0.148**	0.047	0.075	0.107
, .j	(0.115)	(0.118)	(0.085)	(0.034)	(0.078)	(0.061)	(0.053)	(0.047)	(0.300)	(0.140)
10.jobsec	0.488**	0.073	0.205	0.168**	0.023	0.234**	0.655***	0.138*	-0.023	0.275
J	(0.167)	(0.194)	(0.113)	(0.059)	(0.084)	(0.090)	(0.128)	(0.057)	(0.307)	(0.154)
11.jobsec	0.293	0.038	0.090	0.193	-0.124	0.085	0.234***	0.223*	0.012	0.079
J	(0.151)	(0.169)	(0.123)	(0.114)	(0.106)	(0.084)	(0.068)	(0.104)	(0.308)	(0.174)
12.jobsec	0.207	-0.121	0.077	0.093**	-0.015	0.129	0.136**	0.161**	0.213	0.289
J	(0.120)	(0.122)	(0.088)	(0.033)	(0.082)	(0.073)	(0.051)	(0.050)	(0.304)	(0.148)
13.jobsec	0.132	-0.130	0.072	0.070^{*}	-0.139	0.105	0.065	0.064	-0.064	0.024
5	(0.118)	(0.119)	(0.088)	(0.034)	(0.081)	(0.066)	(0.051)	(0.049)	(0.301)	(0.142)
14.jobsec	0.194	-0.116	0.050	0.054	-0.051	0.198^{**}	0.172^{**}	0.061	0.131	0.251
5	(0.121)	(0.128)	(0.096)	(0.041)	(0.087)	(0.068)	(0.059)	(0.052)	(0.302)	(0.162)
15.jobsec	0.129	-0.218	-0.147	-0.041	-0.072	0.026	0.131*	-0.028	-0.088	-0.125
Ū.	(0.161)	(0.119)	(0.116)	(0.093)	(0.108)	(0.077)	(0.059)	(0.062)	(0.307)	(0.145)
16.jobsec	0.263^{*}	0.085	0.207^{*}	0.215***	0.087	0.525^{***}	0.264^{***}	0.148^{**}	0.225	0.299^{*}
	(0.123)	(0.138)	(0.093)	(0.040)	(0.115)	(0.130)	(0.078)	(0.051)	(0.304)	(0.145)
17.jobsec	0.483***	0.215	0.290^{**}	0.149**	0.113	0.238	0.389***	0.182***	0.329	0.211
	(0.139)	(0.135)	(0.091)	(0.048)	(0.146)	(0.122)	(0.087)	(0.055)	(0.306)	(0.147)
18.jobsec	0.183	-0.252	0.290^{**}	0.032	-0.054	-0.067	0.339	0.076	-0.026	0.279
	(0.125)	(0.167)	(0.092)	(0.088)	(0.113)	(0.100)	(0.205)	(0.058)	(0.322)	(0.198)
19.jobsec	0.295^{*}	0.074	0.190^{*}	0.173***	-0.036	-0.008	0.127	0.146^{**}	0.229	0.269
	(0.125)	(0.135)	(0.089)	(0.041)	(0.107)	(0.091)	(0.072)	(0.049)	(0.302)	(0.148)
20.jobsec	0.084	-0.278^{*}	0.016	0.083	-0.311**	0.080	0.097	0.009	-0.105	0.005
	(0.123)	(0.122)	(0.096)	(0.054)	(0.106)	(0.088)	(0.056)	(0.049)	(0.303)	(0.154)
21.jobsec	0.374**	0.071	0.159	0.020	0.063	0.157^{*}	0.293***	-0.007	0.153	0.183
	(0.120)	(0.129)	(0.086)	(0.035)	(0.081)	(0.070)	(0.048)	(0.048)	(0.301)	(0.145)
22.jobsec	0.320**	-0.015	-0.019	-0.118***	-0.155*	-0.115	0.194***	-0.160***	-0.035	-0.224
	(0.124)	(0.126)	(0.088)	(0.033)	(0.078)	(0.068)	(0.054)	(0.047)	(0.301)	(0.143)
23.jobsec	0.226	-0.217	0.077	-0.018	-0.193*	-0.000	0.162**	-0.022	-0.002	0.058
	(0.118)	(0.123)	(0.086)	(0.032)	(0.082)	(0.069)	(0.055)	(0.047)	(0.300)	(0.141)
24.jobsec	0.166	-0.200	0.065	0.056	-0.179	0.104	0.095	-0.081	-0.139	-0.025
25 . 1	(0.133)	(0.186)	(0.107)	(0.074)	(0.109)	(0.119)	(0.123)	(0.064)	(0.311)	(0.175)
25.jobsec	0.037	-0.246	0.119	0.099*	-0.300	0.078	-0.038	0.025	-0.118	0.032
0611	(0.123)	(0.133)	(0.106)	(0.048)	(0.209)	(0.143)	(0.077)	(0.070)	(0.313)	(0.153)
26.jobsec		-0.484***					-0.150		0.266	0.293
07 1		(0.141)					(0.092)		(0.309)	(0.259)
27.jobsec									0.225	
2000	6 525***	9.047***	2 1 1 2***	4.830***	2 122***	0.690***	1.688***	4 905***	(0.301) 1.871***	2.212***
_cons	6.535***		2.112***		2.122^{***}			4.895***		
N	(0.157) 1747	(0.148) 1717	(0.130) 1328	(0.088) 1578	(0.151) 1002	(0.163) 1511	(0.113) 1395	(0.079) 1798	(0.320) 1916	(0.192)
$\frac{N}{R^2}$										1334
<u></u>	0.497	0.533	0.503	0.485	0.526	0.417	0.540	0.513	0.493	0.524

Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Sample: full-time employees aged 35–54. Numeracy score standardized to std. dev. 1 within each country. Experiencesq divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2 . Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001 Full table (C) is presented in the appendix

Table A7. Model 3 Controlling for numeracy scores

Table A7 Effect of firm size on earnings, included numeracy score

	Pooled	Austria	Belgium	Canada	Czech R.	Denmar k	Estonia	Finland	France	German y	Ireland	Italy
l.firmsiz e	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
l 1to 50	0.072***	0.093***	0.012	0.086***	0.085^{**}	0.074***	0.067^{**}	0.076^{***}	0.056**	0.059	0.172***	0.076^{*}
	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)	(0.01)	(0.03)	(0.01)	(0.02)	(0.03)	(0.04)	(0.03)
1 to 250	0.116^{***}	0.133***	0.059^{*}	0.140***	0.107^{**}	0.086***	0.104^{***}	0.141***	0.097***	0.178***	0.223***	0.135**
	(0.01)	(0.03)	(0.02)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)
51to 000	0.182***	0.152***	0.108***	0.225***	0.173***	0.160***	0.185***	0.172***	0.121***	0.229***	0.298***	0.161**
	(0.01)	(0.03)	(0.03)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)	(0.04)	(0.05)
000 +	0.239***	0.161***	0.105^{**}	0.259***	0.191**	0.170^{***}	0.129^{*}	0.203***	0.223***	0.345***	0.215***	0.251**
	(0.02)	(0.03)	(0.03)	(0.02)	(0.06)	(0.02)	(0.06)	(0.03)	(0.03)	(0.04)	(0.06)	(0.05)
umscor 1	0.080***	0.077***	0.078^{***}	0.080***	0.048***	0.064***	0.077***	0.036***	0.073****	0.095****	0.135***	0.059**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
xper	0.014***	-0.001	0.011^{*}	0.012***	0.013^{*}	-0.001	0.015^{**}	0.013***	0.019^{***}	0.011^{*}	0.015	0.011^{*}
•	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
xpersq	-0.021***	0.010	-0.016	-0.019***	-0.019	0.004	-0.029**	-0.022***	-0.026***	-0.006	-0.014	-0.007
1 1	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
.agecoh	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
.agecoh	0.004	0.030	0.025	0.021	-0.040	0.010	-0.038	-0.060**	-0.017	0.007	0.027	0.014
	(0.01)	(0.03)	(0.03)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.014)
.agecoh	-0.007	(0.05)	0.027	(0.02)	-0.085	0.036	-0.145***	-0.029	-0.035	(0.05)	0.052	0.003
	(0.01)		(0.03)		(0.05)	(0.02)	(0.04)	(0.02)	(0.02)		(0.052)	(0.003)
.agecoh	-0.007	0.026	0.065	0.014	-0.080	0.007	(0.04) -0.147 ^{***}	-0.022	-0.036	-0.027	-0.012	0.036
.agecon	(0.01)	(0.03)	(0.04)	(0.014)	(0.05)	(0.02)	(0.04)	(0.022)	(0.03)	(0.04)	(0.06)	(0.030
agaaah	-0.015	0.057	0.084*	0.018	-0.093	0.016	(0.04) -0.169 ^{***}	-0.038	0.002	-0.053	-0.035	-0.016
.agecoh	(0.013)	(0.037	(0.04)	(0.018)	(0.06)	(0.010)	(0.04)	(0.03)	(0.03)	(0.04)	(0.06)	(0.04)
	-0.143***	(0.04) -0.142***	(0.04) -0.054 ^{**}	(0.02) -0.152***	-0.166^{***}	-0.075***	-0.286***	-0.131***	-0.051***	(0.04) -0.098 ^{***}	-0.080**	-0.105
emale												
	(0.02)	(0.02) -0.071**	(0.02)	(0.01)	(0.03)	(0.01) -0.043**	(0.02) -0.112***	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)
nigrant	-0.039*		0.004	-0.017	0.006			-0.041	0.021	-0.010	-0.056	-0.050
• • •	(0.01)	(0.03)	(0.03)	(0.01)	(0.05)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.04)	(0.05)
.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
.jobtyp	-0.070**	0.004	-0.025	-0.020	-0.062	-0.113***	-0.124***	-0.082**	-0.086**	-0.058	0.082	-0.098
	(0.02)	(0.04)	(0.03)	(0.02)	(0.07)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.06)	(0.11)
.jobtyp	-0.231***	-0.174***	-0.134***	-0.207***	-0.193***	-0.186***	-0.305***	-0.299***	-0.290***	-0.293***	-0.120	-0.381
	(0.01)	(0.04)	(0.03)	(0.02)	(0.06)	(0.02)	(0.04)	(0.03)	(0.02)	(0.04)	(0.07)	(0.11)
.jobtyp	-0.357***	-0.349***	-0.229***	-0.363***	-0.288***	-0.253***	-0.449***	-0.438***	-0.400***	-0.342***	-0.268***	-0.529
	(0.02)	(0.04)	(0.03)	(0.03)	(0.06)	(0.03)	(0.05)	(0.03)	(0.03)	(0.04)	(0.07)	(0.11)
i.jobtyp	-0.461***	-0.409***	-0.288***	-0.428***	-0.419***	-0.356***	-0.706***	-0.500***	-0.463***	-0.486***	-0.384***	-0.526
	(0.02)	(0.05)	(0.04)	(0.03)	(0.07)	(0.03)	(0.04)	(0.03)	(0.03)	(0.05)	(0.07)	(0.11)
.jobtyp	-0.439***	-0.290	-0.696***	-0.357***	-0.882***	-0.346***	-0.516***	-0.619***	-0.537***	-0.464***	-0.384*	-0.602
	(0.03)	(0.15)	(0.19)	(0.08)	(0.13)	(0.04)	(0.09)	(0.08)	(0.06)	(0.12)	(0.15)	(0.14)
.jobtyp	-0.382***	-0.375***	-0.303***	-0.249***	-0.374***	-0.310***	-0.404***	-0.497***	-0.418***	-0.483***	-0.187*	-0.560
- 1	(0.03)	(0.04)	(0.04)	(0.03)	(0.07)	(0.03)	(0.05)	(0.03)	(0.03)	(0.04)	(0.08)	(0.11)
.jobtyp	-0.472***	-0.453***	-0.396***	-0.394***	-0.427***	-0.412***	-0.520***	-0.526***	-0.501***	-0.568***	-0.349***	-0.589
	(0.02)	(0.04)	(0.04)	(0.03)	(0.06)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.08)	(0.11)
0.jobty	-0.572***	-0.535***	-0.435***	-0.551***	-0.554***	-0.391***	-0.760***	-0.621***	-0.489***	-0.686***	-0.312***	-0.626
	(0.0.7)			· ·	(a. a	(A. A)		(A. A	10.0-		(A. A)	
	(0.03)	(0.04)	(0.04)	(0.03)	(0.07)	(0.03)	(0.04)	(0.03)	(0.03)	(0.06)	(0.08)	(0.11)
.jobsec	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
.jobsec	0.340***	0.045	0.522^{*}	0.427***	0.294^{**}	0.122	0.330**	0.079	-0.163	0.409^{**}	0.399*	0.291
	(0.04)	(0.18)	(0.25)	(0.06)	(0.10)	(0.09)	(0.11)	(0.10)	(0.10)	(0.14)	(0.19)	(0.21)
.jobsec	0.102^{**}	0.213	0.322	0.116^{**}	0.124	0.026	-0.025	0.030	0.023	0.480***	0.323^{**}	0.238^{*}
	(0.03)	(0.15)	(0.21)	(0.04)	(0.08)	(0.05)	(0.07)	(0.07)	(0.06)	(0.10)	(0.11)	(0.07)
0.jobsec	0.264***	0.411**	0.148	0.502***	0.234*	0.040	0.030	0.155	0.128	0.457***	0.381*	0.283
-	(0.05)	(0.16)	(0.23)	(0.06)	(0.11)	(0.06)	(0.09)	(0.09)	(0.08)	(0.12)	(0.17)	(0.09)
1.jobsec	0.122***	-0.000	0.368	0.135	-0.020	-0.011	0.175	-0.022	0.070	0.453***	0.385**	0.237
5	(0.03)	(0.17)	(0.21)	(0.09)	(0.10)	(0.07)	(0.10)	(0.08)	(0.09)	(0.12)	(0.13)	(0.09)
2.jobsec	0.165***	0.257	0.251	0.236***	0.182	0.030	0.237**	0.107	0.010	0.386***	0.345**	0.139
	(0.03)	(0.15)	(0.21)	(0.05)	(0.09)	(0.05)	(0.08)	(0.07)	(0.06)	(0.10)	(0.13)	(0.08)
3.jobsec	0.027	0.150	0.292	-0.008	0.012	-0.028	0.014	0.050	-0.030	0.321**	0.342**	0.150
5.jobsec	(0.027	(0.15)	(0.292)	-0.008 (0.04)	(0.012)	-0.028 (0.05)	(0.014)	(0.030)	-0.050 (0.06)	(0.321)	(0.342)	(0.07)
	(0.03) 0.115^{***}	0.166									. ,	
1		0.166	0.319	0.131**	0.219^{*}	-0.057	0.124	0.021	0.034	0.294^{**}	0.390^{**}	0.185
4.jobsec			(0.21)	(0.05)	(0.10)	(0,0,0)	(0, 0, 7)	(0.00)	(0,0,0)	(0 1 0)	(0 1 2)	(0.00)
4.jobsec 5.jobsec	(0.03) -0.087*	(0.15) 0.013	(0.21) 0.267	(0.05) -0.139**	(0.10) -0.059	(0.06) -0.048	(0.07) -0.051	(0.08) 0.001	(0.06) -0.058	(0.10) 0.039	(0.13) 0.202	(0.08) 0.135

	(0.04)	(0.15)	(0.21)	(0.05)	(0.10)	(0.06)	(0.09)	(0.08)	(0.07)	(0.13)	(0.12)	(0.09)
16.jobsec	0.192^{***}	0.384^{*}	0.368	0.206^{***}	0.260^{*}	0.049	0.209^{*}	0.067	0.095	0.445^{***}	0.323**	0.228^{*}
-	(0.03)	(0.15)	(0.21)	(0.05)	(0.10)	(0.06)	(0.09)	(0.08)	(0.07)	(0.11)	(0.12)	(0.10)
17.jobsec	0.258^{***}	0.430^{**}	0.439^{*}	0.240^{***}	0.258^{*}	0.155^{**}	0.202^{*}	0.150^{*}	0.136^{*}	0.518^{***}	0.580^{***}	0.494^{***}
	(0.03)	(0.15)	(0.21)	(0.04)	(0.12)	(0.06)	(0.09)	(0.07)	(0.06)	(0.11)	(0.12)	(0.09)
18.jobsec	0.122^{*}	0.362	0.515^{*}	0.048	0.192	0.046	-0.100	-0.048	-0.027	0.359**	0.669^{**}	0.253^{*}
	(0.05)	(0.20)	(0.21)	(0.07)	(0.18)	(0.06)	(0.11)	(0.12)	(0.08)	(0.13)	(0.22)	(0.10)
19.jobsec	0.182^{***}	0.148	0.328	0.227^{***}	0.118	0.078	0.043	0.004	0.050	0.357***	0.595***	0.191^{*}
	(0.03)	(0.16)	(0.21)	(0.05)	(0.10)	(0.05)	(0.09)	(0.07)	(0.07)	(0.11)	(0.12)	(0.09)
20.jobsec	0.006	0.006	0.324	0.052	-0.007	-0.048	0.038	-0.031	-0.079	0.267^{**}	0.302^{*}	0.043
	(0.02)	(0.16)	(0.21)	(0.05)	(0.14)	(0.06)	(0.10)	(0.07)	(0.06)	(0.10)	(0.12)	(0.09)
21.jobsec	0.194^{***}	0.194	0.365	0.343***	0.145	-0.057	0.113	-0.038	-0.040	0.449^{***}	0.440^{***}	0.263***
	(0.05)	(0.15)	(0.21)	(0.04)	(0.09)	(0.05)	(0.07)	(0.07)	(0.06)	(0.10)	(0.12)	(0.07)
22.jobsec	0.059	0.114	0.233	0.230***	-0.000	-0.126*	-0.204**	-0.071	-0.107	0.411***	0.515^{***}	0.078
	(0.06)	(0.15)	(0.21)	(0.04)	(0.09)	(0.05)	(0.07)	(0.07)	(0.06)	(0.10)	(0.11)	(0.07)
23.jobsec	0.094^{*}	0.178	0.307	0.187^{***}	-0.037	-0.127*	0.040	-0.050	-0.081	0.338***	0.359**	0.238^{**}
	(0.03)	(0.15)	(0.20)	(0.04)	(0.11)	(0.05)	(0.07)	(0.07)	(0.06)	(0.10)	(0.11)	(0.07)
24.jobsec	0.003	0.070	0.370	0.151^{**}	-0.224	-0.133*	-0.243**	-0.181^{*}	-0.010	0.247^{*}	0.474^{***}	0.255^{**}
	(0.05)	(0.15)	(0.23)	(0.06)	(0.16)	(0.06)	(0.08)	(0.08)	(0.13)	(0.12)	(0.14)	(0.09)
25.jobsec	0.040	0.239	0.179	0.110	-0.040	-0.089	-0.024	-0.069	-0.024	0.246	0.397^{**}	-0.041
	(0.03)	(0.15)	(0.22)	(0.06)	(0.11)	(0.06)	(0.13)	(0.08)	(0.08)	(0.13)	(0.13)	(0.13)
26.jobsec	-0.078		0.168	0.112				-0.123	-0.255	1.276***		-0.085
	(0.05)		(0.27)	(0.15)				(0.11)	(0.28)	(0.10)		(0.09)
27.jobsec	0.242	0.701^{*}				-0.237***		0.571***	0.014	0.974^{***}		
	(0.15)	(0.30)				(0.07)		(0.07)	(0.15)	(0.10)		
_cons	3.540***	2.604***	2.455***	2.997^{***}	4.779^{***}	5.411***	1.851***	3.032***	2.554^{***}	2.351***	2.277^{***}	2.413***
	(0.06)	(0.16)	(0.21)	(0.06)	(0.11)	(0.07)	(0.10)	(0.08)	(0.08)	(0.12)	(0.16)	(0.13)
Ν	42858	1255	1372	9122	1343	2932	2353	2003	2083	1626	1215	1169
R^2	0.393	0.534	0.400	0.495	0.449	0.433	0.460	0.571	0.490	0.511	0.417	0.444

	Japan	Korea	Netherl.	Norway	Poland	Slova R.	Spain	Sweden	U.K	USA
1.firmsiz	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
e										
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
11to 50	0.067^{*}	0.090^{**}	0.071**	0.056^{**}	0.153***	0.088^{**}	0.041	0.031*	0.154***	0.079^{*}
	(0.031)	(0.032)	(0.026)	(0.020)	(0.035)	(0.032)	(0.028)	(0.014)	(0.034)	(0.040)
51 to 250	0.128***	0.164^{***}	0.139***	0.116^{***}	0.171^{***}	0.097^{**}	0.146***	0.063***	0.164^{***}	0.155***
	(0.032)	(0.035)	(0.026)	(0.022)	(0.034)	(0.034)	(0.031)	(0.015)	(0.035)	(0.041)
251to	0.237***	0.226***	0.179^{***}	0.126^{***}	0.209^{***}	0.141^{***}	0.182^{***}	0.122^{***}	0.241***	0.259^{***}
1000										
	(0.039)	(0.047)	(0.028)	(0.026)	(0.048)	(0.041)	(0.039)	(0.019)	(0.037)	(0.046)
1000 +	0.356***	0.447^{***}	0.203***	0.163***	0.304***	0.221***	0.280^{***}	0.118^{***}	0.300^{***}	0.308^{***}
	(0.043)	(0.053)	(0.036)	(0.026)	(0.055)	(0.051)	(0.041)	(0.021)	(0.038)	(0.049)
numscore 1	0.079***	0.077***	0.086***	0.053***	0.075***	0.102***	0.091***	0.045***	0.100***	0.106***
	(0.012)	(0.014)	(0.011)	(0.007)	(0.014)	(0.015)	(0.015)	(0.007)	(0.012)	(0.016)
exper	0.030***	0.024***	0.002	0.007	0.022***	0.006	0.012*	0.008*	0.014^{*}	0.007
I	(0.005)	(0.005)	(0.006)	(0.004)	(0.006)	(0.008)	(0.005)	(0.003)	(0.006)	(0.007)
expersq	-0.051***	-0.040***	0.002	-0.012	-0.034**	-0.012	-0.014	-0.011*	-0.021*	-0.011
1 1	(0.010)	(0.012)	(0.010)	(0.007)	(0.012)	(0.015)	(0.010)	(0.005)	(0.010)	(0.011)
1.agecoh	0.000	0.000	0.000	0.000	0.000	0.000 [´]	0.000	0.000 [´]	0.000	0.000
e	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2.agecoh	0.049	-0.019	0.110***	0.002	0.040	-0.009	0.039	0.019	-0.006	0.040
U	(0.033)	(0.034)	(0.031)	(0.021)	(0.046)	(0.039)	(0.035)	(0.020)	(0.037)	(0.039)
3.agecoh	-0.002	-0.055	0.085*	0.034	-0.057	0.007	0.052	0.029	-0.005	
e	(0.035)	(0.039)	(0.033)	(0.023)	(0.044)	(0.046)	(0.034)	(0.021)	(0.040)	
4.agecoh	0.061	-0.030	0.077*	0.060^{*}	-0.040	0.005	0.034	0.042	-0.059	0.070
C	(0.042)	(0.039)	(0.033)	(0.024)	(0.049)	(0.050)	(0.035)	(0.022)	(0.041)	(0.040)
5.agecoh	0.052	-0.063	0.083*	0.043	-0.058	0.014	-0.001	0.030	-0.069	0.079
e	(0.040)	(0.044)	(0.037)	(0.027)	(0.053)	(0.057)	(0.040)	(0.023)	(0.045)	(0.047)
female	-0.317***	-0.278***	-0.039	-0.100***	-0.130***	-0.216***	-0.113***	-0.068***	-0.103***	-0.135***
	(0.027)	(0.030)	(0.021)	(0.014)	(0.029)	(0.026)	(0.025)	(0.011)	(0.025)	(0.030)
migrant	0.244***	0.005	-0.058	-0.034	0.000	0.068	-0.034	-0.024	0.028	-0.034
	(0.043)	(0.088)	(0.033)	(0.022)	(.)	(0.093)	(0.046)	(0.015)	(0.034)	(0.038)
2.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5 51	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
3.jobtyp	-0.174***	-0.166*	-0.054	-0.028	-0.166**	-0.126*	-0.108	-0.136***	-0.053	0.014
5 21	(0.044)	(0.065)	(0.028)	(0.023)	(0.059)	(0.063)	(0.074)	(0.021)	(0.041)	(0.042)
4.jobtyp	-0.271***	-0.454***	-0.167***	-0.118***	-0.344***	-0.295***	-0.405***	-0.242***	-0.099*	-0.220***
5 21	(0.040)	(0.068)	(0.030)	(0.024)	(0.058)	(0.060)	(0.080)	(0.022)	(0.042)	(0.046)
5.jobtyp	-0.399***	-0.338***	-0.351***	-0.272***	-0.593***	-0.428***	-0.451***	-0.377***	-0.379***	-0.506***
5 71	(0.043)	(0.063)	(0.034)	(0.032)	(0.067)	(0.068)	(0.078)	(0.028)	(0.044)	(0.050)
6.jobtyp	-0.483***	-0.650***	-0.354***	-0.273***	-0.693***	-0.647***	-0.582***	-0.343***	-0.430***	-0.541***
- J - J F										

	(0, 0.16)	(0, 0.67)	(0.027)	(0.028)	(0, 062)	$(0, 0, \epsilon, \epsilon)$	(0.078)	(0.022)	(0, 0.12)	(0.050)
7.1.	(0.046)	(0.067)	(0.037)	(0.028)	(0.063)	(0.066)	(0.078)	(0.023)	(0.043)	(0.050)
7.jobtyp	-0.386**	-0.357	-0.620***	-0.607	-0.742***	-0.569***	-0.584***	-0.443***	-0.512***	-0.287
	(0.126)	(0.188)	(0.113)	(0.354)	(0.148)	(0.089)	(0.091)	(0.062)	(0.151)	(0.335)
8.jobtyp	-0.512***	-0.541***	-0.368***	-0.267***	-0.644***	-0.506***	-0.508***	-0.373***	-0.338***	-0.399***
	(0.046)	(0.067)	(0.035)	(0.030)	(0.060)	(0.068)	(0.085)	(0.028)	(0.048)	(0.058)
9.jobtyp	-0.554***	-0.664***	-0.456***	-0.312***	-0.617***	-0.583***	-0.564***	-0.399***	-0.471***	-0.624***
	(0.051)	(0.070)	(0.052)	(0.038)	(0.066)	(0.065)	(0.086)	(0.031)	(0.047)	(0.057)
10.jobtyp	-0.536***	-0.731***	-0.476***	-0.322***	-0.682***	-0.687***	-0.681***	-0.486***	-0.583***	-0.606***
	(0.086)	(0.066)	(0.046)	(0.043)	(0.060)	(0.067)	(0.080)	(0.032)	(0.047)	(0.091)
7.jobsec	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
8.jobsec	0.368^{**}	0.155	0.455***	0.384***	0.218	0.062	0.332^{*}	0.283***	0.287	0.654^{*}
-	(0.130)	(0.149)	(0.086)	(0.054)	(0.117)	(0.124)	(0.157)	(0.081)	(0.271)	(0.259)
9.jobsec	0.259*	-0.128	0.045	0.085*	-0.090	0.077	0.188***	0.023	0.055	0.175
5	(0.118)	(0.123)	(0.077)	(0.038)	(0.088)	(0.065)	(0.055)	(0.048)	(0.183)	(0.156)
10.jobsec	0.476**	0.118	0.195	0.136*	-0.026	0.220*	0.621***	0.111	-0.056	0.336
	(0.175)	(0.200)	(0.111)	(0.063)	(0.095)	(0.093)	(0.152)	(0.059)	(0.204)	(0.174)
11.jobsec	0.326*	0.048	0.044	0.064	-0.177	0.087	0.240**	0.184	0.045	0.085
11,000,000	(0.148)	(0.176)	(0.115)	(0.144)	(0.118)	(0.085)	(0.081)	(0.100)	(0.192)	(0.189)
12.jobsec	0.241	-0.084	0.027	0.061	-0.062	0.142	0.153**	0.134**	0.169	0.334*
12.j00500	(0.124)	(0.126)	(0.081)	(0.037)	(0.091)	(0.077)	(0.050)	(0.051)	(0.188)	(0.163)
13.jobsec	0.174	-0.090	0.017	0.036	-0.162	0.118	0.077	0.037	-0.101	0.078
15.j00300	(0.121)	(0.124)	(0.080)	(0.037)	(0.092)	(0.070)	(0.049)	(0.049)	(0.184)	(0.157)
14.jobsec	0.211	-0.082	-0.009	0.015	-0.080	0.186*	0.204***	0.041	0.094	0.309
14.j00300	(0.123)	(0.132)	(0.089)	(0.045)	(0.098)	(0.073)	(0.060)	(0.041)	(0.184)	(0.169)
15.jobsec	0.125)	-0.205	-0.174	-0.050	-0.103	0.039	0.175**	-0.052	-0.070	-0.066
15.J00sec	(0.145)	(0.124)	(0.106)	(0.095)	(0.119)	(0.080)	(0.056)	(0.052)	(0.191)	(0.160)
16.jobsec	(0.102) 0.289^*	0.124)	0.153	(0.093) 0.178***	0.121	0.580***	0.258**	0.121*	0.184	0.364*
16.Jobsec										
17:	(0.126) 0.524 ^{***}	(0.144)	(0.087)	(0.044)	(0.120)	(0.126) 0.294*	(0.086) 0.408^{***}	(0.052)	(0.192)	(0.161)
17.jobsec		0.251	0.208*	0.124*	0.154			0.155**	0.281	0.315
10 1 1	(0.145)	(0.139)	(0.084)	(0.053)	(0.158)	(0.115)	(0.086)	(0.056)	(0.194)	(0.161)
18.jobsec	0.185	-0.210	0.252**	0.031	-0.077	-0.052	0.306	0.070	-0.012	0.450*
10 1	(0.134)	(0.172)	(0.084)	(0.092)	(0.110)	(0.140)	(0.242)	(0.058)	(0.218)	(0.182)
19.jobsec	0.319*	0.149	0.171*	0.164***	-0.009	0.052	0.184*	0.133**	0.213	0.381*
	(0.128)	(0.139)	(0.082)	(0.044)	(0.110)	(0.091)	(0.080)	(0.050)	(0.189)	(0.162)
20.jobsec	0.117	-0.257*	-0.001	0.042	-0.322**	0.095	0.119*	-0.006	-0.118	0.063
	(0.126)	(0.126)	(0.087)	(0.054)	(0.121)	(0.089)	(0.055)	(0.049)	(0.188)	(0.167)
21.jobsec	0.411***	0.121	0.113	0.005	0.086	0.211**	0.355***	-0.011	0.131	0.288
	(0.122)	(0.133)	(0.077)	(0.039)	(0.091)	(0.074)	(0.048)	(0.049)	(0.185)	(0.159)
22.jobsec	0.398**	0.044	-0.024	-0.112**	-0.122	-0.058	0.256^{***}	-0.153**	-0.020	-0.040
	(0.128)	(0.131)	(0.080)	(0.037)	(0.088)	(0.071)	(0.054)	(0.048)	(0.187)	(0.158)
23.jobsec	0.272^{*}	-0.165	0.076	-0.013	-0.213*	0.016	0.209^{***}	-0.019	0.024	0.164
	(0.121)	(0.127)	(0.079)	(0.037)	(0.091)	(0.073)	(0.055)	(0.048)	(0.185)	(0.157)
24.jobsec	0.191	-0.138	0.069	0.020	-0.123	0.120	0.175	-0.095	-0.116	0.102
	(0.137)	(0.190)	(0.108)	(0.068)	(0.114)	(0.128)	(0.137)	(0.064)	(0.198)	(0.178)
25.jobsec	0.091	-0.201	0.100	0.073	-0.391*	0.046	-0.008	-0.003	-0.071	0.131
	(0.129)	(0.136)	(0.099)	(0.052)	(0.194)	(0.130)	(0.072)	(0.073)	(0.202)	(0.166)
26.jobsec		-0.460***					-0.064		0.312	0.192
		(0.138)					(0.087)		(0.200)	(0.189)
27.jobsec									0.200	
•									(0.186)	
_cons	7.056***	9.592***	2.811***	5.358***	2.892***	1.578^{***}	2.194^{***}	5.189***	2.396***	2.902^{***}
	(0.136)	(0.137)	(0.104)	(0.066)	(0.114)	(0.119)	(0.099)	(0.063)	(0.197)	(0.182)
N	1747	1717	1328	1579	1002	1511	1396	1798	2106	1506
R^2	0.497	0.523	0.478	0.466	0.503	0.402	0.513	0.509	0.514	0.490
. .		1.1.1.1.1	11	11. D	1	1 1 1 1		1 0 11 12		1.05.54

Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Sample: full-time employees aged 35–54. Numeracy score standardized to std. dev. 1 within each country. Experiencesq divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R2 refers to within-country R2. Robust standard errors in parentheses.

Table A8. Model 4 Full model

Table Ao II	U	2	and education									
	Pooled	Austria	Belgium	Canada	Czech R.	Denmar k	Estonia	Finland	France	German y	Ireland	Italy
1.firmsiz e	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
11to 50	0.068***	0.098***	0.006	0.083***	0.082**	0.069***	0.064*	0.072***	0.046*	0.048	0.164***	0.065*
	(0.005)	(0.025)	(0.023)	(0.018)	(0.030)	(0.015)	(0.025)	(0.014)	(0.018)	(0.035)	(0.040)	(0.032)
51 to 250	0.108***	0.136***	0.052*	0.136***	0.102**	0.075***	0.098***	0.135***	0.091***	0.161***	0.206***	0.119***
	(0.006)	(0.026)	(0.024)	(0.018)	(0.035)	(0.015)	(0.027)	(0.016)	(0.019)	(0.035)	(0.043)	(0.035)
251to 1000	0.170***	0.159***	0.100***	0.213***	0.166***	0.154***	0.165***	0.167***	0.106***	0.216***	0.273***	0.147**
	(0.008)	(0.028)	(0.026)	(0.019)	(0.041)	(0.019)	(0.034)	(0.020)	(0.021)	(0.039)	(0.044)	(0.045)
1000 +	0.222^{***}	0.156^{***}	0.097^{**}	0.236^{***}	0.189^{***}	0.147^{***}	0.116^{*}	0.200^{***}	0.213***	0.330***	0.197^{***}	0.225***
	(0.016)	(0.033)	(0.032)	(0.022)	(0.053)	(0.019)	(0.055)	(0.027)	(0.026)	(0.041)	(0.055)	(0.050)
umscor 1	0.056***	0.053***	0.058***	0.060***	0.027	0.042***	0.062***	0.024**	0.048***	0.081***	0.101***	0.041**
	(0.003)	(0.010)	(0.009)	(0.008)	(0.015)	(0.006)	(0.011)	(0.007)	(0.008)	(0.013)	(0.020)	(0.013)
educ	0.030* ^{***}	0.039***	0.026***	0.024 ^{***}	0.032***	0.029***	0.026***	0.024***	0.021***	0.023***	0.032***	0.021***
	(0.002)	(0.004)	(0.004)	(0.003)	(0.006)	(0.003)	(0.004)	(0.003)	(0.002)	(0.006)	(0.005)	(0.006)
exper	0.015***	0.004	0.012^{*}	0.013 ^{***}	0.016^{*}	0.003	0.016**	0.014***	0.018***	0.013*	0.014	0.011*
1	(0.002)	(0.006)	(0.005)	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.004)	(0.005)	(0.008)	(0.005)
expersq	-0.021 ****	0.004	-0.012	-0.018**	-0.021	0.001	-0.029***	-0.020 ****	-0.021**	-0.010	-0.011	-0.003
1 1	(0.004)	(0.012)	(0.010)	(0.006)	(0.012)	(0.004)	(0.010)	(0.006)	(0.007)	(0.010)	(0.016)	(0.011)
l.agecoh	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2.agecoh	0.002	0.032	0.018	0.019	-0.047	0.009	-0.045	-0.058**	-0.003	0.004	0.030	0.016
-	(0.007)	(0.027)	(0.027)	(0.019)	(0.043)	(0.019)	(0.033)	(0.022)	(0.022)	(0.032)	(0.041)	(0.035)
3.agecoh	-0.010		0.016		-0.096*	0.033	-0.167***	-0.033	-0.016		0.055	0.001
U	(0.013)		(0.030)		(0.046)	(0.019)	(0.037)	(0.024)	(0.023)		(0.047)	(0.035)
4.agecoh	-0.012	0.012	0.046	0.009	-0.092	-0.003	-0.173***	-0.028	-0.023	-0.030	-0.005	0.036
•	(0.013)	(0.030)	(0.034)	(0.019)	(0.050)	(0.020)	(0.039)	(0.026)	(0.027)	(0.036)	(0.056)	(0.041)
5.agecoh	-0.025	0.043	0.044	0.009	-0.116*	-0.007	-0.205***	-0.051	0.017	-0.061	-0.025	-0.022
•	(0.013)	(0.035)	(0.040)	(0.020)	(0.058)	(0.022)	(0.045)	(0.028)	(0.030)	(0.040)	(0.053)	(0.042)
female	-0.141***	-0.117***	-0.056***	-0.145***	-0.138***	-0.076***	-0.286***	-0.134***	-0.060***	-0.092***	-0.091**	-0.114**
	(0.017)	(0.021)	(0.016)	(0.013)	(0.028)	(0.011)	(0.022)	(0.013)	(0.014)	(0.023)	(0.029)	(0.025)
migrant	-0.067***	-0.106***	0.005	-0.043**	-0.021	-0.064***	-0.119***	-0.071*	0.021	-0.009	-0.080^{*}	-0.065
U	(0.017)	(0.025)	(0.033)	(0.015)	(0.053)	(0.016)	(0.025)	(0.035)	(0.022)	(0.032)	(0.035)	(0.048)
2.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
3.jobtyp	-0.083***	-0.030	-0.026	-0.028	-0.075	-0.113***	-0.134***	-0.077**	-0.085**	-0.089**	0.060	-0.115
	(0.018)	(0.037)	(0.033)	(0.021)	(0.064)	(0.021)	(0.036)	(0.025)	(0.027)	(0.033)	(0.061)	(0.113)
4.jobtyp	-0.205***	-0.125***	-0.111****	-0.188 ***	-0.152**	-0.159***	-0.279***	-0.255***	-0.251***	-0.253***	-0.125	-0.343**
	(0.013)	(0.036)	(0.033)	(0.022)	(0.059)	(0.023)	(0.040)	(0.025)	(0.024)	(0.037)	(0.065)	(0.110)
5.jobtyp	-0.317***	-0.268***	-0.187***	-0.339***	-0.238***	-0.204***	-0.403***	-0.372***	-0.356***	-0.289***	-0.249***	-0.469**
	(0.022)	(0.041)	(0.034)	(0.025)	(0.064)	(0.026)	(0.049)	(0.028)	(0.027)	(0.042)	(0.071)	(0.112)
5.jobtyp	-0.403***	-0.333***	-0.238***	-0.397***	-0.341***	-0.296***	-0.647***	-0.410***	-0.413***	-0.427***	-0.336***	-0.435**
	(0.023)	(0.045)	(0.039)	(0.026)	(0.070)	(0.027)	(0.041)	(0.030)	(0.030)	(0.048)	(0.067)	(0.116)
7.jobtyp	-0.372***	-0.232	-0.681 ***	-0.315***	-0.870 ****	-0.284 ***	-0.455 ***	-0.510***	-0.482***	-0.413***	-0.375*	-0.503**
	(0.027)	(0.153)	(0.179)	(0.081)	(0.132)	(0.045)	(0.090)	(0.075)	(0.053)	(0.125)	(0.151)	(0.142)
8.jobtyp	-0.318***	-0.313***	-0.255***	-0.214***	-0.298***	-0.256***	-0.335***	-0.402***	-0.356***	-0.417***	-0.165^{*}	-0.462**
-	(0.021)	(0.041)	(0.037)	(0.029)	(0.072)	(0.026)	(0.048)	(0.032)	(0.030)	(0.043)	(0.076)	(0.118)
9.jobtyp	-0.395***	-0.364***	-0.328***	-0.352***	-0.351***	-0.330***	-0.449***	-0.423***	-0.432***	-0.499***	-0.280***	-0.482**
	(0.016)	(0.044)	(0.042)	(0.033)	(0.067)	(0.031)	(0.045)	(0.036)	(0.030)	(0.045)	(0.081)	(0.119)
10.jobty	-0.485***	-0.400***	-0.360***	-0.508***	-0.471***	-0.305***	-0.688***	-0.514***	-0.412***	-0.589***	-0.258***	-0.517**
)												
	(0.030)	(0.045)	(0.043)	(0.029)	(0.069)	(0.029)	(0.046)	(0.035)	(0.031)	(0.064)	(0.074)	(0.116)
7.jobsec	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
8.jobsec	0.330***	0.022	0.517^{*}	0.432***	0.286^{**}	0.110	0.321**	0.090	-0.157	0.408^{**}	0.337^{*}	0.272
	(0.039)	(0.179)	(0.229)	(0.061)	(0.103)	(0.091)	(0.105)	(0.089)	(0.096)	(0.143)	(0.160)	(0.202)
).jobsec	0.094^{**}	0.197	0.340	0.129**	0.114	0.039	-0.035	0.033	0.016	0.482^{***}	0.250^{*}	0.226^{***}
	(0.032)	(0.159)	(0.194)	(0.043)	(0.089)	(0.053)	(0.067)	(0.069)	(0.056)	(0.098)	(0.103)	(0.067)
10.jobsec	0.245***	0.354^{*}	0.182	0.509^{***}	0.237^{*}	0.057	0.002	0.124	0.107	0.455***	0.361*	0.239^{**}
	(0.054)	(0.165)	(0.219)	(0.062)	(0.116)	(0.064)	(0.087)	(0.086)	(0.081)	(0.117)	(0.152)	(0.088)
11.jobsec	0.111**	-0.061	0.373	0.126	-0.001	-0.001	0.151	-0.021	0.063	0.448^{***}	0.272^{*}	0.222**
	(0.033)	(0.170)	(0.200)	(0.095)	(0.103)	(0.068)	(0.098)	(0.077)	(0.083)	(0.121)	(0.129)	(0.086)
	0.160***	0.247	0.268	0.256***	0.172	0.048	0.216**	0.114	0.026	0.379***	0.270^{*}	0.133
12.jobsec		(0.1.(1))	(0, 107)	(0.049)	(0.097)	(0.055)	(0.078)	(0.071)	(0.059)	(0.101)	(0.124)	(0.081)
12.jobsec	(0.029)	(0.161)	(0.197)	(0.049)	(0.077)	(0.055)	(0.070)	(0.071)	(0.00))		(0.12.)	(0.001)
	(0.029) 0.020	(0.161) 0.133	0.298	0.007	-0.012	-0.010	-0.002	0.051	-0.033	0.320**	0.284**	0.132*
12.jobsec 13.jobsec		. ,	. ,		· /	. ,	. ,	. ,				

	(0.025)	(0, 1, (2))	(0.100)	(0.047)	(0,000)	(0.050)	(0.072)	(0.07.4)	(0,0,c,1)	(0.105)	(0.100)	(0,000)
1 1	(0.025)	(0.162)	(0.196)	(0.047)	(0.099)	(0.059)	(0.073)	(0.074)	(0.061)	(0.105)	(0.128)	(0.080)
15.jobsec	-0.087*	0.010	0.278	-0.110*	-0.083	-0.050	-0.058	-0.004	-0.062	0.026	0.132	0.120
	(0.037)	(0.163)	(0.200)	(0.048)	(0.105)	(0.060)	(0.094)	(0.073)	(0.069)	(0.134)	(0.109)	(0.095)
16.jobsec	0.178^{***}	0.404^{*}	0.368	0.214***	0.211^{*}	0.062	0.209^{*}	0.080	0.072	0.452***	0.249^{*}	0.217^{*}
	(0.025)	(0.162)	(0.199)	(0.050)	(0.101)	(0.058)	(0.092)	(0.073)	(0.065)	(0.108)	(0.114)	(0.094)
17.jobsec	0.241***	0.435**	0.434^{*}	0.242^{***}	0.199	0.160^{**}	0.175	0.138	0.116	0.529^{***}	0.505***	0.479^{***}
	(0.030)	(0.160)	(0.196)	(0.044)	(0.131)	(0.057)	(0.089)	(0.072)	(0.062)	(0.109)	(0.110)	(0.096)
18.jobsec	0.105^{*}	0.320	0.503^{*}	0.059	0.175	0.042	-0.115	-0.024	-0.048	0.339**	0.650^{**}	0.176
	(0.046)	(0.205)	(0.196)	(0.071)	(0.178)	(0.062)	(0.110)	(0.114)	(0.080)	(0.127)	(0.203)	(0.109)
19.jobsec	0.150***	0.114	0.325	0.223***	0.080	0.071	0.010	-0.005	0.024	0.342^{**}	0.509***	0.170^{*}
	(0.031)	(0.166)	(0.196)	(0.048)	(0.107)	(0.055)	(0.092)	(0.070)	(0.064)	(0.106)	(0.111)	(0.085)
20.jobsec	-0.003	0.002	0.340	0.058	-0.026	-0.022	0.010	-0.037	-0.077	0.274^{**}	0.257^{*}	0.022
	(0.024)	(0.167)	(0.197)	(0.054)	(0.141)	(0.061)	(0.097)	(0.071)	(0.061)	(0.103)	(0.112)	(0.083)
21.jobsec	0.167^{**}	0.165	0.366	0.339***	0.092	-0.063	0.082	-0.044	-0.050	0.437***	0.361**	0.218^{**}
	(0.049)	(0.158)	(0.195)	(0.043)	(0.091)	(0.054)	(0.072)	(0.070)	(0.056)	(0.102)	(0.111)	(0.071)
22.jobsec	0.016	0.066	0.221	0.203***	-0.048	-0.135*	-0.230***	-0.097	-0.130^{*}	0.402^{***}	0.399***	0.052
U U	(0.056)	(0.159)	(0.196)	(0.043)	(0.096)	(0.054)	(0.069)	(0.070)	(0.057)	(0.102)	(0.107)	(0.069)
23.jobsec	0.068	0.121	0.304	0.183***	-0.056	-0.125^{*}	0.020	-0.072	-0.092	0.320^{**}	0.271^{*}	0.225^{**}
U U	(0.034)	(0.160)	(0.194)	(0.042)	(0.113)	(0.054)	(0.072)	(0.069)	(0.057)	(0.101)	(0.105)	(0.074)
24.jobsec	-0.018	0.035	0.365	0.134^{*}	-0.256	-0.106	-0.258**	-0.171*	-0.034	0.260^{*}	0.412^{**}	0.208^*
U U	(0.046)	(0.161)	(0.216)	(0.055)	(0.166)	(0.062)	(0.084)	(0.074)	(0.130)	(0.113)	(0.141)	(0.092)
25.jobsec	0.016	0.198	0.195	0.108	-0.070	-0.099	-0.056	-0.076	-0.034	0.235	0.323*	-0.057
5	(0.027)	(0.160)	(0.205)	(0.061)	(0.105)	(0.061)	(0.129)	(0.074)	(0.074)	(0.129)	(0.125)	(0.123)
26.jobsec	-0.077		0.185	0.098				-0.152	0.112	1.260***		-0.096
5	(0.050)		(0.250)	(0.146)				(0.120)	(0.115)	(0.104)		(0.091)
27.jobsec	0.198	0.605^{*}	. ,	. ,		-0.254***		0.568***	-0.045	0.889***		· · · ·
5	(0.147)	(0.291)				(0.073)		(0.071)	(0.135)	(0.104)		
_cons	3.117***	2.014***	2.060^{***}	2.646***	4.277***	4.936***	1.515***	2.636***	2.271***	1.972***	1.859***	2.117***
_ `	(0.069)	(0.180)	(0.212)	(0.071)	(0.149)	(0.080)	(0.114)	(0.092)	(0.079)	(0.159)	(0.166)	(0.167)
Ν	42424	1255	1371	9080	1342	2932	2353	2003	2076	1607	1215	1169
R^2	0.410	0.567	0.420	0.503	0.467	0.466	0.468	0.591	0.511	0.517	0.434	0.458

	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.	USA
1.firmsize	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
11to 50	0.061^{*}	0.077^{*}	0.066^{**}	0.051^{*}	0.145***	0.081^{*}	0.040	0.027	0.162***	0.091^{*}
	(0.030)	(0.031)	(0.026)	(0.020)	(0.035)	(0.032)	(0.026)	(0.014)	(0.037)	(0.042)
51 to 250	0.123***	0.127^{***}	0.128^{***}	0.105***	0.140^{***}	0.075^{*}	0.140^{***}	0.054^{***}	0.169^{***}	0.170^{***}
	(0.032)	(0.035)	(0.025)	(0.022)	(0.034)	(0.033)	(0.029)	(0.015)	(0.038)	(0.042)
251to 1000	0.228***	0.182***	0.166***	0.108***	0.197***	0.127**	0.160^{***}	0.118***	0.242***	0.260***
1000	(0.029)	(0,04c)	(0.029)	(0.020)	(0.047)	(0.041)	(0,02c)	(0.010)	(0,040)	(0.040)
1000	(0.038) 0.344***	(0.046) 0.395***	(0.028) 0.186^{***}	(0.026) 0.150***	(0.047) 0.278***	(0.041) 0.199^{***}	(0.036) 0.255***	(0.019) 0.111 ^{***}	(0.040) 0.294 ^{***}	(0.049) 0.328***
1000 +										
	(0.042) 0.062***	(0.050) 0.050***	(0.035) 0.055***	(0.026) 0.038***	(0.054) 0.050^{***}	(0.051) 0.077***	(0.042) 0.052***	(0.020) 0.032***	(0.040) 0.086^{***}	(0.050) 0.060^{***}
numscore	0.062	0.050	0.055	0.038	0.050	0.077	0.052	0.032	0.086	0.060
1	(0.010)	(0.01.0)	(0.010)	(0,000)	(0.01.1)	(0.015)	(0.015)	(0.007)	(0.010)	(0.010)
1	(0.013) 0.029***	(0.014) 0.034^{***}	(0.010)	(0.008) 0.029^{***}	(0.014)	(0.015)	(0.015) 0.035***	(0.007) 0.017^{***}	(0.013) 0.029***	(0.018) 0.045^{***}
educ			0.038***		0.046***	0.046***				
	(0.006)	(0.005)	(0.004)	(0.004)	(0.007)	(0.006)	(0.004)	(0.003)	(0.005)	(0.006)
exper	0.032***	0.024***	0.003	0.008*	0.019***	0.009	0.013*	0.009**	0.019**	0.008
	(0.005)	(0.005)	(0.005)	(0.004)	(0.006)	(0.008)	(0.005)	(0.003)	(0.007)	(0.007)
expersq	-0.050***	-0.037**	0.005	-0.012	-0.025*	-0.013	-0.011	-0.010	-0.029*	-0.013
	(0.010)	(0.012)	(0.009)	(0.007)	(0.012)	(0.016)	(0.010)	(0.005)	(0.011)	(0.012)
1.agecoh	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2.agecoh	0.043	-0.020	0.092**	-0.002	0.037	-0.011	0.031	0.013	-0.009	0.035
	(0.033)	(0.033)	(0.030)	(0.021)	(0.044)	(0.038)	(0.034)	(0.020)	(0.038)	(0.040)
3.agecoh	-0.007	-0.054	0.087^{**}	0.024	-0.044	-0.003	0.050	0.017	-0.021	
	(0.035)	(0.039)	(0.031)	(0.022)	(0.042)	(0.046)	(0.033)	(0.021)	(0.041)	
4.agecoh	0.046	-0.023	0.064^{*}	0.048^{*}	-0.033	-0.021	0.025	0.024	-0.068	0.041
	(0.042)	(0.039)	(0.032)	(0.024)	(0.047)	(0.049)	(0.035)	(0.022)	(0.042)	(0.042)
5.agecoh	0.022	-0.030	0.050	0.023	-0.057	-0.024	-0.004	0.006	-0.067	0.060
	(0.039)	(0.044)	(0.036)	(0.027)	(0.050)	(0.056)	(0.039)	(0.024)	(0.046)	(0.049)
female	-0.296***	-0.247***	-0.036	-0.098***	-0.127***	-0.205***	-0.122***	-0.071***	-0.107***	-0.117**
	(0.027)	(0.030)	(0.020)	(0.013)	(0.028)	(0.026)	(0.024)	(0.011)	(0.025)	(0.032)
migrant	0.327***	-0.012	-0.077^{*}	-0.059**	0.000	0.039	-0.057	-0.029*	0.005	-0.043
	(0.046)	(0.088)	(0.033)	(0.022)	(.)	(0.097)	(0.047)	(0.014)	(0.035)	(0.040)
2.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
3.jobtyp	-0.187***	-0.174**	-0.074**	-0.047*	-0.178**	-0.105	-0.107	-0.146***	-0.075	-0.039
	(0.042)	(0.062)	(0.026)	(0.022)	(0.055)	(0.062)	(0.071)	(0.020)	(0.041)	(0.041)

R^2	0.506	0.537	0.514	0.493	0.533	0.430	0.546	0.519	0.513	0.530
Ν	1747	1717	1328	1578	1002	1511	1395	1798	1916	1334
	(0.158)	(0.151)	(0.128)	(0.090)	(0.152)	(0.164)	(0.111)	(0.078)	(0.296)	(0.197)
_cons	6.626***	9.122***	2.226***	4.870***	2.213****	0.801***	1.730***	4.942***	(0.274) 1.875***	2.301***
27.jobsec		(0.150)					(0.074)		0.267	(0.242)
26.jobsec		-0.497*** (0.138)					-0.143 (0.094)		0.341 (0.279)	0.324 (0.242)
-	(0.126)	(0.134)	(0.104)	(0.052)	(0.203)	(0.128)	(0.074)	(0.070)	(0.288)	(0.156)
25.jobsec	0.066	-0.268*	0.088	0.107*	-0.338	0.040	-0.048	0.025	-0.045	0.062
2 1.jobsee	(0.135)	(0.187)	(0.106)	(0.075)	(0.110)	(0.125)	(0.112)	(0.064)	(0.282)	(0.178)
24.jobsec	(0.120) 0.190	(0.125) -0.228	(0.084) 0.045	(0.039) 0.051	(0.084) -0.192	(0.070) 0.095	(0.053) 0.112	(0.046) -0.080	(0.274) -0.020	(0.146) 0.008
23.jobsec	0.254*	-0.236	0.065	0.001	-0.206^{*}	-0.010	0.148^{**}	-0.013	0.079	0.100
aa · 1	(0.126)	(0.128)	(0.086)	(0.040)	(0.080)	(0.069)	(0.052)	(0.047)	(0.275)	(0.147)
22.jobsec	0.340**	-0.042	-0.048	-0.104**	-0.182*	-0.117	0.180***	-0.151**	0.018	-0.179
-1.900000	(0.122)	(0.131)	(0.083)	(0.041)	(0.083)	(0.071)	(0.046)	(0.048)	(0.274)	(0.149)
21.jobsec	0.385**	0.038	0.128	0.028	0.043	0.155*	0.276***	-0.005	0.204	0.216
20.jobsec	(0.125)	-0.304 (0.124)	-0.004 (0.093)	(0.088)	-0.333 (0.111)	(0.078)	(0.086)	(0.012)	-0.025 (0.277)	(0.157)
20.jobsec	(0.127) 0.098	(0.137) -0.304*	(0.087) -0.004	(0.046) 0.088	(0.105) -0.333**	(0.089) 0.078	(0.074) 0.086	(0.048) 0.012	(0.276) -0.025	(0.152) 0.039
19.jobsec	0.298*	0.050	0.153	0.178^{***}	-0.070	-0.011	0.117	0.142^{**}	0.279	0.293
10 1	(0.127)	(0.170)	(0.089)	(0.090)	(0.107)	(0.113)	(0.208)	(0.057)	(0.299)	(0.197)
18.jobsec	0.183	-0.271	0.253**	0.047	-0.088	-0.079	0.327	0.081	0.067	0.299
	(0.143)	(0.137)	(0.088)	(0.053)	(0.147)	(0.123)	(0.084)	(0.055)	(0.280)	(0.151)
17.jobsec	0.496***	0.140)	0.249**	0.153**	0.086	0.230	0.360***	0.177**	0.359	0.237
16.jobsec	(0.270 (0.125)	(0.140)	(0.163 (0.091)	(0.212 (0.046)	0.057 (0.113)	(0.512 (0.125)	0.233 (0.077)	0.144 (0.051)	0.266 (0.278)	0.305 (0.149)
16 jobsoc	(0.162) 0.270^*	(0.121) 0.053	(0.114) 0.163	(0.092) 0.212***	(0.112)	(0.079) 0.512 ^{***}	(0.058) 0.233**	(0.060) 0.144^{**}	(0.279) 0.266	(0.150) 0.305*
15.jobsec	0.156	-0.240*	-0.160	-0.020	-0.101	0.019	0.131*	-0.037	0.018	-0.066
1 1	(0.123)	(0.130)	(0.093)	(0.047)	(0.090)	(0.070)	(0.057)	(0.051)	(0.275)	(0.166)
14.jobsec	0.200	-0.148	0.013	0.064	-0.090	0.179*	0.159**	0.056	0.194	0.277
-	(0.120)	(0.122)	(0.085)	(0.040)	(0.084)	(0.066)	(0.049)	(0.048)	(0.274)	(0.146)
13.jobsec	0.154	-0.155	0.043	0.079*	-0.171*	0.097	0.043	0.058	0.005	0.052
	(0.123)	(0.124)	(0.086)	(0.039)	(0.084)	(0.074)	(0.049)	(0.049)	(0.277)	(0.152)
12.jobsec	0.226	-0.141	0.049	0.098*	-0.040	0.133	0.123*	0.159**	0.263	0.316*
11.jobsec	0.318 [*] (0.151)	0.009 (0.172)	0.038 (0.117)	0.183 (0.108)	-0.143 (0.106)	0.055 (0.084)	0.229 ^{***} (0.067)	0.231 [*] (0.115)	0.094 (0.279)	0.088 (0.177)
11 johana	(0.168)	(0.198)	(0.110)	(0.063)	(0.087)	(0.093)	(0.123) 0.220***	(0.057)	(0.283)	(0.161)
10.jobsec	0.482**	0.045	0.184	0.164**	0.006	0.209*	0.630***	0.129*	0.058	0.274
-	(0.118)	(0.120)	(0.083)	(0.040)	(0.080)	(0.062)	(0.052)	(0.047)	(0.273)	(0.144)
9.jobsec	0.236*	-0.172	0.069	0.128**	-0.089	0.078	0.136**	0.043	0.142	0.133
0.100500	(0.129)	(0.131)	(0.090)	(0.054)	(0.108)	(0.122)	(0.159)	(0.078)	(0.351)	(0.236)
8.jobsec	(.) 0.398**	(.) 0.087	(.) 0.418 ^{***}	(.) 0.407***	(.) 0.215*	(.) 0.083	(.) 0.252	(.) 0.328***	(.) 0.227	(.) 0.757**
7.jobsec	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.086)	(0.066)	(0.047)	(0.046)	(0.065)	(0.072)	(0.081)	(0.035)	(0.050)	(0.094)
10.jobtyp	-0.475***	-0.610***	-0.404***	-0.264***	-0.492***	-0.480***	-0.532***	-0.444***	-0.574***	-0.508***
- J J I	(0.052)	(0.070)	(0.052)	(0.038)	(0.070)	(0.069)	(0.086)	(0.031)	(0.051)	(0.063)
9.jobtyp	-0.492***	-0.557***	-0.368***	-0.264***	-0.443***	-0.411***	-0.403***	-0.377***	-0.457***	-0.527***
8.J00typ	(0.047)	(0.066)	(0.035)	(0.030)	(0.062)	(0.071)	(0.083)	(0.028)	(0.049)	(0.063)
8.jobtyp	(0.121) -0.452***	(0.186) -0.441***	-0.311***	-0.237***	(0.154) -0.485***	(0.091) -0.338***	-0.365***	-0.354***	(0.174) -0.299 ^{***}	-0.330***
7.jobtyp	-0.336^{**}	-0.255	-0.558*** (0.108)	-0.530 (0.376)	-0.498^{**}	-0.387^{***}	-0.451*** (0.095)	-0.411*** (0.060)	-0.468** (0.174)	-0.157 (0.282)
- • • •	(0.046)	(0.065)	(0.037)	(0.028)	(0.063)	(0.069)	(0.077)	(0.025)	(0.045)	(0.055)
6.jobtyp	-0.449***	-0.574***	-0.293***	-0.228***	-0.561***	-0.493***	-0.454***	-0.311***	-0.378***	-0.498***
	(0.042)	(0.061)	(0.033)	(0.033)	(0.064)	(0.070)	(0.076)	(0.028)	(0.045)	(0.057)
5.jobtyp	(0.039) -0.372***	(0.067) -0.299***	(0.028) -0.304***	(0.024) -0.216 ^{***}	(0.056) -0.504***	(0.060) -0.311***	(0.077) -0.371***	(0.022) -0.354***	-0.355***	(0.047) -0.463***
									(0.042)	

Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Sample: full-time employees aged 35-54. Numeracy score standardized to std. dev. 1 within each country. Experiencesq divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R2 refers to within-country R2. Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Table A9. Model 5 Interaction between numeracy and firm-size

Table A9

Table A9												
	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland	Italy
1.firmsiz	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
e	(.)	()	(.)	()	()	()	()	()	()	(.)	()	()
11to 50	0.073***	(.) 0.095***	0.009	(.) 0.085***	(.) 0.083**	(.) 0.074 ^{****}	(.) 0.069**	(.) 0.076 ^{***}	(.) 0.055**	0.060	(.) 0.172***	(.) 0.072*
1100 00	(0.006)	(0.026)	(0.024)	(0.018)	(0.031)	(0.015)	(0.025)	(0.015)	(0.019)	(0.035)	(0.039)	(0.033)
51 to 250	0.118***	0.140***	0.055*	0.138***	0.109**	0.080***	0.103***	0.140***	0.099***	0.180***	0.219***	0.127***
	(0.007)	(0.027)	(0.024)	(0.018)	(0.037)	(0.016)	(0.028)	(0.016)	(0.019)	(0.035)	(0.042)	(0.037)
251to	0.181^{***}	0.157^{***}	0.106^{***}	0.222^{***}	0.177^{***}	0.161***	0.191***	0.172^{***}	0.114^{***}	0.231***	0.276^{***}	0.152^{**}
1000												(0.0.10)
1000	(0.009)	(0.029)	(0.027)	(0.020)	(0.042) 0.197^{***}	(0.020)	(0.035)	(0.022)	(0.022)	(0.039)	(0.044)	(0.049)
1000 +	0.238^{***}	0.154*** (0.035)	0.086^{**}	0.265^{***}		0.139^{***}	0.129^{*}	0.209^{***}	0.209^{***}	0.360^{***}	0.223^{***}	0.233***
numscor	(0.015) 0.067^{***}	0.049**	(0.033) 0.041	(0.023) 0.074 ^{***}	(0.059) 0.036	(0.024) 0.042^{**}	$(0.056) \\ 0.048^{*}$	(0.030) 0.039^{**}	(0.026) 0.052**	(0.045) 0.079^*	(0.062) 0.227***	(0.050) 0.068 ^{**}
el	0.007	0.047	0.041	0.074	0.050	0.042	0.040	0.037	0.052	0.077	0.227	0.000
••	(0.005)	(0.019)	(0.023)	(0.014)	(0.022)	(0.014)	(0.022)	(0.014)	(0.017)	(0.036)	(0.042)	(0.023)
exper	0.014***	0.000	0.015***	0.013***	0.007	0.001	0.004	0.011***	0.015***	0.008	0.019*	0.012*
-	(0.002)	(0.006)	(0.005)	(0.003)	(0.005)	(0.002)	(0.005)	(0.003)	(0.003)	(0.005)	(0.007)	(0.005)
expersq	-0.021***	0.011	-0.017^{*}	-0.020***	-0.014	0.001	-0.018^{*}	-0.020***	-0.016*	-0.006	-0.026	-0.011
~	(0.003)	(0.011)	(0.009)	(0.005)	(0.011)	(0.004)	(0.009)	(0.005)	(0.007)	(0.009)	(0.014)	(0.010)
firmnum	0.019**	0.031	0.039	0.012	0.009	0.015	0.045	0.005	0.019	0.063	-0.154**	-0.018
score2	(0.006)	(0.022)	(0.026)	(0.019)	(0.032)	(0.017)	(0.026)	(0.016)	(0.020)	(0.041)	(0.047)	(0.035)
firmnum	0.013	0.022)	0.042	0.019)	0.024	0.036*	0.020)	-0.011	0.020)	(0.041) -0.004	(0.047) -0.125 [*]	-0.014
score3	0.010	0.000	0.012	0.012	0.021	0.000	0.0.0	0.011	0.020	0.001	0.120	0.011
	(0.007)	(0.023)	(0.026)	(0.018)	(0.029)	(0.018)	(0.028)	(0.017)	(0.020)	(0.039)	(0.054)	(0.034)
firmnum	0.021**	0.037	0.046	0.010	0.020	0.015	0.025	0.002	0.042	0.013	-0.073	-0.010
score4	(0.007)	(0.05.5	(0.07-5)	(0.017)	(0.055)	(0.07.1)	(0.05	(0.05.1)	(0.055)	(0.0.1.1)	(0.0	(0.0-5)
c	(0.007)	(0.026)	(0.029)	(0.019)	(0.033)	(0.021)	(0.035)	(0.021)	(0.022)	(0.041)	(0.052)	(0.052)
firmnum score5	0.019^{*}	0.064^{*}	0.064*	-0.013	0.030	0.073**	-0.009	-0.036	0.061*	-0.013	-0.115	-0.006
scores	(0.009)	(0.031)	(0.033)	(0.021)	(0.047)	(0.026)	(0.046)	(0.041)	(0.027)	(0.046)	(0.068)	(0.045)
female	-0.144***	-0.134***	-0.053**	-0.152***	-0.175***	-0.072***	-0.293***	-0.132***	-0.054***	-0.103***	-0.088**	-0.106***
	(0.019)	(0.021)	(0.016)	(0.013)	(0.028)	(0.012)	(0.022)	(0.013)	(0.014)	(0.023)	(0.029)	(0.025)
migrant	-0.040*	-0.060*	0.011	-0.015	0.003	-0.041*	-0.120***	-0.043	0.019	-0.010	-0.064	-0.054
	(0.015)	(0.025)	(0.034)	(0.014)	(0.050)	(0.016)	(0.025)	(0.034)	(0.022)	(0.031)	(0.036)	(0.050)
2.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2:14	(.)	(.)	(.)	(.)	(.)	(.) -0.117 ^{***}	(.)	(.)	(.)	(.)	(.)	(.)
3.jobtyp	-0.070 ^{***} (0.018)	-0.001 (0.040)	-0.026 (0.034)	-0.021 (0.021)	-0.055 (0.065)	(0.022)	-0.127*** (0.036)	-0.082** (0.027)	-0.085** (0.028)	-0.057 (0.033)	0.080 (0.060)	-0.096 (0.109)
4.jobtyp	-0.231***	-0.183***	-0.133***	-0.206***	-0.185**	-0.186***	-0.301***	-0.301***	-0.288***	-0.281***	-0.130*	-0.378***
njootyp	(0.014)	(0.037)	(0.034)	(0.022)	(0.056)	(0.023)	(0.040)	(0.027)	(0.024)	(0.035)	(0.066)	(0.105)
5.jobtyp	-0.356***	-0.354***	-0.232***	-0.362***	-0.285***	-0.255***	-0.449***	-0.439***	-0.393***	-0.333***	-0.280***	-0.526***
	(0.020)	(0.041)	(0.034)	(0.025)	(0.062)	(0.026)	(0.049)	(0.030)	(0.027)	(0.040)	(0.072)	(0.108)
6.jobtyp	-0.461***	-0.418***	-0.290***	-0.426***	-0.413 ****	-0.360***	-0.712***	-0.501***	-0.464***	-0.472***	-0.386 ^{****}	-0.521***
	(0.023)	(0.046)	(0.039)	(0.025)	(0.067)	(0.027)	(0.041)	(0.030)	(0.030)	(0.047)	(0.067)	(0.108)
7.jobtyp	-0.439***	-0.294*	-0.689***	-0.358***	-0.836***	-0.347***	-0.519***	-0.620****	-0.544***	-0.458***	-0.382*	-0.603***
8.jobtyp	(0.031) -0.381***	(0.149) -0.379 ^{***}	(0.198) -0.307***	(0.081) -0.248***	(0.132) -0.373***	(0.045) -0.313***	(0.091) -0.402***	(0.076) -0.499***	(0.055) -0.420***	(0.119) -0.472***	(0.159) -0.190 [*]	(0.138) -0.553***
5.ј65тур	(0.029)	(0.041)	(0.036)	(0.029)	(0.069)	(0.026)	(0.048)	(0.032)	(0.029)	(0.040)	(0.075)	(0.110)
9.jobtyp	-0.471***	-0.457***	-0.395***	-0.392***	-0.416***	-0.413***	-0.524***	-0.532***	-0.500***	-0.560***	-0.365***	-0.588***
	(0.018)	(0.044)	(0.040)	(0.032)	(0.064)	(0.030)	(0.045)	(0.034)	(0.029)	(0.041)	(0.078)	(0.110)
10.jobtyp	-0.572***	-0.542***	-0.428***	-0.548***	-0.547***	-0.393***	-0.772***	-0.623***	-0.492***	-0.683***	-0.332***	-0.623****
- · ·	(0.028)	(0.045)	(0.042)	(0.028)	(0.066)	(0.027)	(0.045)	(0.035)	(0.030)	(0.057)	(0.072)	(0.106)
7.jobsec	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
8.jobsec	(.) 0.343***	(.) 0.042	(.) 0.532*	(.) 0.426***	(.) 0.287**	(.) 0.136	(.) 0.352**	(.) 0.078	(.) -0.158	(.) 0.404**	(.) 0.431*	(.) 0.295
8.JU08ec	(0.0343)	(0.176)	(0.244)	(0.062)	(0.105)	(0.086)	(0.108)	(0.099)	(0.108)	(0.137)	(0.192)	(0.202)
9.jobsec	0.104**	0.212	0.315	0.116**	0.131	0.027	0.001	0.029	0.026	0.477***	0.328**	0.231**
×.j	(0.032)	(0.148)	(0.199)	(0.043)	(0.083)	(0.053)	(0.068)	(0.072)	(0.057)	(0.095)	(0.107)	(0.070)
10.jobsec	0.265***	0.414^{**}	0.138	0.502^{***}	0.244^{*}	0.043	0.051	0.153	0.132	0.453***	0.389^{*}	0.271**
	(0.052)	(0.156)	(0.224)	(0.061)	(0.113)	(0.064)	(0.088)	(0.090)	(0.083)	(0.115)	(0.164)	(0.088)
11.jobsec	0.123***	-0.018	0.363	0.133	-0.021	-0.007	0.204*	-0.030	0.072	0.457***	0.391**	0.227*
10 1	(0.031)	(0.167)	(0.207)	(0.094)	(0.098)	(0.070)	(0.103)	(0.080)	(0.085)	(0.118)	(0.135)	(0.089)
12.jobsec	0.167^{***}	0.250	0.237	0.235^{***}	0.199^{*}	0.033	0.259^{***}	0.105	0.009	0.381***	0.334^{*}	0.129
13.jobsec	(0.027) 0.029	(0.150) 0.148	(0.202) 0.288	(0.049) -0.008	(0.092) 0.020	(0.055) -0.026	(0.078) 0.040	(0.075) 0.049	(0.059) -0.024	(0.099) 0.315 ^{**}	(0.130) 0.327**	(0.084) 0.142^*
13.100.00	(0.030)	(0.148)	(0.200)	(0.043)	(0.020)	(0.055)	(0.040)	(0.073)	(0.058)	(0.097)	(0.110)	(0.069)
14.jobsec	0.117***	0.162	0.314	0.131**	0.232*	-0.056	0.151*	0.026	0.036	0.288**	0.374**	0.179*
·	(0.024)	(0.152)	(0.201)	(0.047)	(0.094)	(0.058)	(0.074)	(0.076)	(0.061)	(0.102)	(0.131)	(0.082)
15.jobsec	-0.087^{*}	0.000	0.239	-0.138**	-0.050	-0.046	-0.027	0.002	-0.060	0.053	0.194	0.128

	(0.039)	(0.154)	(0.207)	(0.049)	(0.099)	(0.061)	(0.093)	(0.076)	(0.069)	(0.131)	(0.116)	(0.096)
16 johaaa	0.193***	(0.134) 0.387^*	0.370	0.206***	(0.099) 0.264**	0.057	(0.093) 0.225*	0.067	(0.069) 0.097	(0.131) 0.441^{***}	(0.110) 0.325^{**}	(0.096) 0.220^*
16.jobsec												
17.1	(0.027)	(0.153)	(0.204)	(0.051)	(0.102)	(0.059)	(0.094)	(0.076)	(0.066)	(0.105)	(0.119)	(0.102)
17.jobsec	0.260***	0.431**	0.438*	0.240***	0.251*	0.157**	0.239**	0.148	0.134*	0.514***	0.583***	0.483***
10 . 1	(0.032)	(0.150)	(0.201)	(0.045)	(0.123)	(0.057)	(0.090)	(0.075)	(0.063)	(0.107)	(0.115)	(0.094)
18.jobsec	0.124*	0.373	0.476*	0.044	0.198	0.045	-0.070	-0.053	-0.030	0.353**	0.652***	0.251*
10 . 1	(0.046)	(0.199)	(0.201)	(0.073)	(0.176)	(0.061)	(0.106)	(0.118)	(0.083)	(0.127)	(0.194)	(0.102)
19.jobsec	0.184***	0.155	0.330	0.226***	0.132	0.079	0.069	0.002	0.056	0.356***	0.587***	0.179*
a a	(0.031)	(0.159)	(0.202)	(0.049)	(0.100)	(0.055)	(0.093)	(0.073)	(0.064)	(0.104)	(0.113)	(0.088)
20.jobsec	0.007	0.011	0.329	0.051	-0.009	-0.046	0.069	-0.032	-0.074	0.268**	0.301*	0.034
	(0.024)	(0.159)	(0.203)	(0.053)	(0.134)	(0.061)	(0.098)	(0.073)	(0.062)	(0.101)	(0.117)	(0.087)
21.jobsec	0.196***	0.196	0.362	0.344***	0.153	-0.055	0.133	-0.040	-0.034	0.443***	0.436***	0.253***
	(0.047)	(0.148)	(0.200)	(0.044)	(0.084)	(0.055)	(0.073)	(0.073)	(0.056)	(0.101)	(0.114)	(0.072)
22.jobsec	0.059	0.118	0.232	0.230***	0.002	-0.124*	-0.182**	-0.076	-0.099	0.397***	0.517***	0.068
	(0.056)	(0.150)	(0.201)	(0.044)	(0.090)	(0.054)	(0.069)	(0.073)	(0.058)	(0.100)	(0.110)	(0.071)
23.jobsec	0.095^{**}	0.185	0.307	0.186***	-0.029	-0.125^{*}	0.067	-0.052	-0.075	0.328^{***}	0.346**	0.229^{**}
	(0.033)	(0.150)	(0.199)	(0.043)	(0.109)	(0.054)	(0.072)	(0.072)	(0.058)	(0.099)	(0.110)	(0.073)
24.jobsec	0.004	0.070	0.376	0.152^{**}	-0.222	-0.133*	-0.223**	-0.186^{*}	-0.009	0.237^{*}	0.452^{**}	0.247^{**}
	(0.047)	(0.153)	(0.219)	(0.059)	(0.164)	(0.062)	(0.084)	(0.078)	(0.129)	(0.114)	(0.140)	(0.095)
25.jobsec	0.042	0.240	0.190	0.109	-0.035	-0.087	0.001	-0.074	-0.018	0.241	0.421***	-0.056
	(0.027)	(0.151)	(0.209)	(0.062)	(0.108)	(0.061)	(0.133)	(0.078)	(0.078)	(0.131)	(0.126)	(0.133)
26.jobsec	-0.087		0.150	0.113				-0.122	-0.272	1.288^{***}		-0.085
	(0.050)		(0.278)	(0.151)				(0.110)	(0.275)	(0.103)		(0.092)
27.jobsec	0.244	0.695^{*}				-0.241***		0.576^{***}	0.035	0.942^{***}		
-	(0.150)	(0.314)				(0.071)		(0.073)	(0.151)	(0.099)		
_cons	3.540***	2.586***	2.415***	2.997^{***}	4.808^{***}	5.404***	1.921***	3.023***	2.575***	2.376***	2.278^{***}	2.421***
	(0.057)	(0.160)	(0.209)	(0.058)	(0.111)	(0.067)	(0.093)	(0.083)	(0.072)	(0.121)	(0.149)	(0.131)
Ν	42872	1256	1372	9125	1344	2932	2354	2003	2083	1626	1215	1169
R^2	0.393	0.535	0.399	0.495	0.447	0.435	0.456	0.569	0.490	0.513	0.425	0.443

	Japan	Korea	Netherl.	Norway	Poland	Slovak.	Spain	Sweden	U.K.	USA
.firmsize	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
1to 50	0.070*	0.093**	0.074**	0.054**	0.151***	0.086**	0.038	0.030*	0.156***	0.070
110 50	(0.031)	(0.031)	(0.026)	(0.020)	(0.036)	(0.033)	(0.029)	(0.014)	(0.035)	(0.039)
1 to 250	0.127***	0.161***	0.134***	0.113***	0.166***	0.099**	0.137***	0.060***	0.163***	0.153***
1 to 250	(0.032)	(0.035)	(0.026)	(0.022)	(0.036)	(0.034)	(0.031)	(0.015)	(0.035)	(0.040)
251to	0.230***	0.200***	0.176***	0.126***	0.203***	0.126**	0.162***	0.118***	0.232***	0.260***
.000	0.230	0.200	0.170	0.120	0.203	0.120	0.102	0.118	0.232	0.200
000	(0.041)	(0.049)	(0.029)	(0.027)	(0.049)	(0.041)	(0.040)	(0.020)	(0.037)	(0.047)
000	0.368***	(0.049) 0.398***	(0.029) 0.200^{***}	(0.027) 0.168^{***}	0.303***	0.236***	(0.040) 0.264^{***}	0.121***	0.311***	0.305***
000+		0.07.0	0.200		0.000		0.20.			
	(0.051)	(0.056)	(0.037)	(0.028)	(0.054)	(0.051)	(0.048)	(0.020)	(0.040)	(0.053)
umscore	0.080***	0.023	0.060**	0.041*	0.051	0.100***	0.077***	0.039**	0.071**	0.100^{*}
	(0.020)	(0.025)	(0.022)	(0.017)	(0.028)	(0.029)	(0.021)	(0.012)	(0.026)	(0.039)
xper	0.032***	0.024***	0.007	0.011^{**}	0.020***	0.005	0.015**	0.011 ^{***}	0.013*	0.009
1	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.007)	(0.005)	(0.003)	(0.005)	(0.006)
xpersq	-0.052****	-0.044 ***	-0.006	-0.017*	-0.036**	-0.010	-0.021*	-0.015***	-0.023*	-0.011
r1	(0.009)	(0.011)	(0.008)	(0.007)	(0.011)	(0.013)	(0.010)	(0.005)	(0.009)	(0.011)
irmnums ore2	-0.014	0.067*	0.005	0.018	0.038	0.007	0.015	-0.001	0.018	0.075
	(0.028)	(0.031)	(0.026)	(0.019)	(0.036)	(0.037)	(0.030)	(0.016)	(0.032)	(0.044)
irmnums ore3	0.001	0.098**	0.043	0.018	0.037	-0.012	0.025	0.019	0.046	-0.036
0165	(0.029)	(0.035)	(0,02c)	(0.021)	(0.036)	(0.042)	(0.024)	(0,01c)	(0.033)	(0.040)
	· · ·		(0.026)	(0.021)	()	(0.042)	(0.034)	(0.016)		(0.046)
irmnums ore4	0.036	0.114^{*}	0.049	0.013	0.027	0.042	0.041	0.022	0.067*	-0.026
	(0.038)	(0.049)	(0.027)	(0.025)	(0.049)	(0.047)	(0.049)	(0.020)	(0.034)	(0.055)
irmnums ore5	-0.007	0.129**	0.037	-0.002	-0.011	-0.034	0.032	-0.009	0.010	0.012
	(0.037)	(0.046)	(0.032)	(0.025)	(0.052)	(0.055)	(0.045)	(0.019)	(0.037)	(0.055)
emale	-0.309***	-0.287***	-0.039	-0.100***	-0.132***	-0.216***	-0.109***	-0.066***	-0.110***	-0.131*
	(0.025)	(0.029)	(0.021)	(0.014)	(0.029)	(0.026)	(0.025)	(0.011)	(0.024)	(0.029)
nigrant	0.218***	0.024	-0.055	-0.030	0.000	0.070	-0.036	-0.021	0.028	-0.031
	(0.040)	(0.095)	(0.033)	(0.022)	(.)	(0.094)	(0.045)	(0.014)	(0.034)	(0.038)
.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Joordh	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
jobtyp	(.) -0.179 ^{***}	(.)-0.160 [*]	-0.055	-0.025	(.) -0.160 ^{**}	(.) -0.124 [*]	-0.118	-0.134***	-0.064	0.011
Jobtyp	(0.043)	(0.063)	-0.033	(0.023)	(0.058)	(0.063)	(0.073)	(0.021)	(0.041)	(0.011)
jobtyp	(0.043) -0.274 ^{***}	(0.063) -0.434 ^{***}	(0.028) -0.168***	(0.023) -0.118 ^{***}	(0.058) -0.342***	(0.063) -0.293***	(0.073) -0.411***	(0.021) -0.240***	(0.041) -0.104 [*]	(0.041) -0.221*
.jobtyp										
· :- 1. 4	(0.040) -0.403***	(0.066) -0.324***	(0.030) -0.356***	(0.024) -0.265***	(0.057) -0.594***	(0.060) -0.426***	(0.080) -0.454***	(0.022) -0.376***	(0.042) -0.385***	(0.046) -0.505*
.jobtyp	-0.403	-0.324	-0.336	-0.265	-0.594	-0.426	-0.454	-0.5/6	-0.385	-0.505

 K^{-} 0.4970.5270.4750.4630.5010.4040.5120.5090.5140.494Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Sample: full-time employees aged 35–54.Numeracy score standardized to std. dev. 1 within each country. Experiencesq divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R2 refers to within-country R2. Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Table A10. Model 6 Interaction between firm size and numeracy

Table A10

	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland	Italy
.firmsize	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1. 50	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
1to 50	-0.049	-0.002	-0.009	-0.075	0.384^{*}	0.021	-0.136	0.100	0.054	-0.477*	0.470^{*}	0.013
1 to 250	(0.030) -0.004	(0.111) 0.070	(0.119) -0.020	(0.092) 0.023	(0.166) 0.306	(0.077) -0.116	(0.126) -0.213	(0.071) 0.242^{***}	(0.059) 0.124 [*]	(0.195) -0.101	(0.222) 0.289	(0.098 0.163
1 10 250	(0.034)	(0.117)	(0.112)	(0.023	(0.163)	(0.081)	(0.133)	(0.073)	(0.059)	(0.201)	(0.227)	(0.103
51to	0.010	0.185	-0.143	0.101	0.629**	0.131	-0.157	0.243**	-0.031	-0.101	0.509*	0.064
000	0.010	0.105	0.145	0.101	0.027	0.151	0.157	0.245	0.051	0.101	0.507	0.004
000	(0.045)	(0.128)	(0.134)	(0.107)	(0.220)	(0.102)	(0.160)	(0.085)	(0.070)	(0.190)	(0.258)	(0.136
000+	0.115	0.050	0.021	0.247^{*}	-0.059	0.045	-0.564*	0.231*	0.229^{*}	0.468^{*}	0.036	0.350*
	(0.055)	(0.148)	(0.142)	(0.117)	(0.281)	(0.099)	(0.241)	(0.103)	(0.095)	(0.195)	(0.333)	(0.176
duc	0.029***	0.040^{***}	0.026***	0.024***	0.051***	0.027***	0.012	0.030***	0.026***	0.014	0.052***	0.024^{*}
	(0.003)	(0.007)	(0.008)	(0.006)	(0.010)	(0.005)	(0.008)	(0.005)	(0.004)	(0.013)	(0.013)	(0.007
xper	0.016^{***}	0.006	0.017^{***}	0.015^{***}	0.009	0.005^{*}	0.003	0.013***	0.016^{***}	0.012^{*}	0.020^{**}	0.015^{*}
	(0.002)	(0.006)	(0.004)	(0.003)	(0.005)	(0.002)	(0.005)	(0.003)	(0.003)	(0.005)	(0.007)	(0.005
xpersq	-0.025***	-0.000	-0.019^{*}	-0.023***	-0.016	-0.005	-0.017	-0.020***	-0.016^{*}	-0.015	-0.026	-0.012
	(0.003)	(0.011)	(0.008)	(0.006)	(0.010)	(0.004)	(0.009)	(0.005)	(0.007)	(0.009)	(0.013)	(0.010
irmeduc2	0.009^{***}	0.009	0.002	0.012	-0.023	0.004	0.017	-0.002	-0.001	0.040^{**}	-0.021	0.006
	(0.002)	(0.009)	(0.009)	(0.007)	(0.012)	(0.006)	(0.010)	(0.005)	(0.005)	(0.014)	(0.014)	(0.008
irmeduc3	0.009**	0.006	0.006	0.009	-0.015	0.015*	0.026*	-0.008	-0.003	0.020	-0.006	-0.003
. <u>.</u> .	(0.003)	(0.009)	(0.009)	(0.007)	(0.012)	(0.006)	(0.010)	(0.006)	(0.005)	(0.015)	(0.015)	(0.009
irmeduc4	0.013**	-0.001	0.020	0.009	-0.034*	0.002	0.027*	-0.006	0.011	0.025	-0.015	0.009
· · -	(0.003)	(0.010)	(0.010)	(0.008)	(0.017)	(0.008)	(0.012)	(0.006)	(0.006)	(0.014)	(0.016)	(0.011
irmeduc5	0.009*	0.009	0.007	0.001	0.019	0.009	0.054**	-0.002	-0.001	-0.006	0.010	-0.010
_	(0.004)	(0.011)	(0.011)	(0.008)	(0.020)	(0.007)	(0.019)	(0.007)	(0.008)	(0.014)	(0.020)	(0.014
emale	-0.155***	-0.126***	-0.070***	-0.160***	-0.161***	-0.087***	-0.309***	-0.140***	-0.070***	-0.123***	-0.125***	-0.114
	(0.018)	(0.020)	(0.016)	(0.013)	(0.026)	(0.011)	(0.021)	(0.013)	(0.013)	(0.022)	(0.029)	(0.024
nigrant	-0.093***	-0.135***	-0.023	-0.072***	-0.039	-0.091***	-0.133***	-0.095**	-0.003	-0.046	-0.087*	-0.080
• • .	(0.015)	(0.023)	(0.032)	(0.015)	(0.051)	(0.015)	(0.025)	(0.034)	(0.021)	(0.032)	(0.035)	(0.047
.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
• • •	(.)	(.)	(.)	(.)	(.)	(.) 0.11 <i>c</i> ***	(.)	(.) 0.07 <i>c</i> **	(.)	(.)	(.)	(.)
.jobtyp	-0.085***	-0.036	-0.040	-0.027	-0.071	-0.116***	-0.149***	-0.076**	-0.087**	-0.102^{**}	0.062	-0.119
:-1	(0.018) -0.210***	(0.038)	(0.033) -0.123***	(0.021) -0.190***	(0.064)	(0.021) -0.165***	(0.036) -0.296***	(0.025)	(0.027) -0.260***	(0.032) -0.259***	(0.062)	(0.115
.jobtyp		-0.132***			-0.148*			-0.263***			-0.126	-0.346
:- h +	(0.014) -0.325***	(0.037)	(0.034) -0.207***	(0.022) -0.351***	(0.060) -0.242***	(0.023) -0.205***	(0.040) -0.439***	(0.025) -0.381***	(0.024) -0.371***	(0.036) -0.294***	(0.067) -0.259***	(0.112
.jobtyp	-0.323 (0.023)	-0.282*** (0.041)	(0.035)	(0.025)		-0.203 (0.026)		(0.028)	(0.028)	-0.294 (0.042)	-0.239 (0.073)	
ichtun	(0.023) - 0.422^{***}	(0.041) -0.361***	(0.055) - 0.260^{***}	(0.023) -0.420***	(0.065) -0.336***	-0.311***	(0.049) -0.691***	(0.028) - 0.422^{***}	-0.437***	(0.042) -0.457***	-0.352***	(0.114 -0.441
.jobtyp	-0.422 (0.024)		(0.039)	-0.420 (0.026)	-0.336 (0.072)	(0.027)		-0.422 (0.030)	(0.030)	-0.437 (0.047)	-0.332 (0.070)	
ichtun	(0.024) -0.399 ^{***}	(0.046) -0.243	(0.039) -0.728 ^{**}	-0.337***	(0.072) - 0.868^{***}	-0.288***	(0.041) -0.495***	-0.533***	-0.550***	(0.047) -0.481***	-0.385*	(0.118 -0.515
.jobtyp	(0.030)	-0.243 (0.158)	(0.228)	-0.337 (0.077)	(0.133)	-0.288 (0.046)	(0.091)	-0.333 (0.074)	(0.053)	(0.136)	(0.159)	(0.147
.jobtyp	(0.030) -0.340***	-0.353***	-0.283***	-0.232***	-0.315***	-0.275***	-0.378***	(0.074) -0.415 ^{***}	-0.386***	-0.448***	(0.139) -0.196 [*]	-0.460
Jobtyp	(0.021)	(0.041)	(0.037)	(0.030)	(0.073)	(0.026)	(0.049)	(0.032)	(0.030)	(0.043)	(0.079)	(0.120
.jobtyp	-0.420***	-0.396***	-0.359***	-0.377***	-0.367***	-0.352***	(0.049) -0.492 ^{***}	-0.439***	-0.465***	-0.535***	-0.335***	-0.496
.jootyp	(0.017)	(0.044)	(0.042)	(0.033)	(0.069)	(0.031)	(0.045)	(0.035)	(0.030)	(0.044)	(0.086)	(0.121
0.jobtyp	-0.519***	-0.445***	-0.413***	-0.545***	-0.493***	-0.330***	(0.045) -0.756 ^{***}	-0.534***	-0.443***	(0.044) -0.641***	-0.307***	-0.525
0.j00typ	(0.030)	(0.045)	(0.044)	(0.030)	(0.070)	(0.028)	(0.046)	(0.035)	(0.031)	(0.062)	(0.076)	(0.118
.jobsec	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
.100300	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
jobsec	0.345***	0.027	0.501*	0.457***	0.300**	0.141	0.351**	0.078	-0.165	0.400**	0.394*	0.329
.,	(0.039)	(0.190)	(0.246)	(0.059)	(0.102)	(0.096)	(0.331)	(0.090)	(0.104)	(0.145)	(0.162)	(0.184
.jobsec	0.107**	0.212	0.364	0.147***	0.119	0.055	0.011	0.027	-0.006	0.470***	0.255*	0.223
.jobsee	(0.030)	(0.171)	(0.208)	(0.040)	(0.089)	(0.054)	(0.068)	(0.070)	(0.055)	(0.100)	(0.111)	(0.068
0.jobsec	0.263***	0.365*	0.214	0.530***	0.248*	0.080	0.068	0.117	0.088	0.471***	0.421**	0.228
o.joosee	(0.052)	(0.175)	(0.227)	(0.066)	(0.118)	(0.065)	(0.088)	(0.086)	(0.081)	(0.120)	(0.145)	(0.088
1.jobsec	0.120**	-0.049	0.390	0.147	-0.004	0.008	0.183	-0.037	0.026	0.430***	0.178	0.215
1.100000	(0.031)	(0.180)	(0.213)	(0.094)	(0.102)	(0.069)	(0.103)	(0.081)	(0.081)	(0.125)	(0.137)	(0.087
2.jobsec	0.168***	0.252	0.273	0.269***	0.180	0.061	0.253**	0.110	-0.006	0.369***	0.255*	0.117
	(0.028)	(0.172)	(0.211)	(0.047)	(0.096)	(0.056)	(0.079)	(0.073)	(0.058)	(0.104)	(0.130)	(0.082
3.jobsec	0.032	0.141	0.311	0.021	-0.006	0.006	0.056	0.051	-0.058	0.312**	0.257*	0.135
	(0.028)	(0.171)	(0.209)	(0.040)	(0.092)	(0.056)	(0.071)	(0.071)	(0.056)	(0.102)	(0.111)	(0.066
4.jobsec	0.119***	0.162	0.354	0.153***	0.224*	-0.015	0.152*	0.029	0.000	0.270*	0.351**	0.185
	(0.022)	(0.174)	(0.210)	(0.044)	(0.098)	(0.060)	(0.074)	(0.02)	(0.060)	(0.107)	(0.131)	(0.079
	-0.091^*	0.009	0.281	-0.098*	-0.082	-0.035	-0.014	-0.011	-0.104	0.030	0.094	0.112
5. jobsec		(0.175)	(0.214)	(0.047)	(0.106)	(0.062)	(0.095)	(0.074)	(0.068)	(0.141)	(0.116)	(0.095
5.jobsec	(0.036)			(0.07/)	(0.100)				· · · ·			
	(0.036) 0.199***			0.243***	0.221^{*}	0.081	0.276**	0.078	0.044	0.464^{***}	0.271^{*}	0.226
5.jobsec 6.jobsec	0.199***	0.425*	0.393	0.243***	0.221^{*}	0.081 (0.059)	0.276^{**}	0.078 (0.074)	0.044 (0.065)	0.464^{***}	0.271^{*} (0.122)	0.226*
				0.243*** (0.048) 0.264***	0.221* (0.099) 0.203	0.081 (0.059) 0.178 ^{**}	0.276** (0.095) 0.266**	0.078 (0.074) 0.129	0.044 (0.065) 0.093	0.464*** (0.111) 0.527***	0.271* (0.122) 0.533****	0.226 [*] (0.097 0.486 [*]

18.jobsec	0.114*	0.346	0.484*	0.089	0.172	0.052	-0.061	-0.029	-0.084	0.297*	0.711***	0.122
10 1	(0.044)	(0.212)	(0.210)	(0.069)	(0.169)	(0.063)	(0.107)	(0.116)	(0.079)	(0.128)	(0.194)	(0.110)
19.jobsec	0.169***	0.128	0.363	0.249***	0.098	0.090	0.083	-0.009	0.006	0.351**	0.519***	0.166
20 1	(0.030)	(0.178)	(0.210)	(0.046)	(0.105)	(0.056)	(0.094)	(0.071)	(0.063)	(0.109)	(0.118)	(0.086)
20.jobsec	0.006	0.007	0.361	0.075	-0.020	-0.006	0.066	-0.040	-0.098	0.257*	0.263*	0.029
	(0.023)	(0.180)	(0.211)	(0.052)	(0.140)	(0.062)	(0.098)	(0.071)	(0.061)	(0.107)	(0.121)	(0.081)
21.jobsec	0.175**	0.166	0.383	0.361***	0.105	-0.051	0.125	-0.052	-0.074	0.412***	0.367**	0.202**
	(0.049)	(0.170)	(0.209)	(0.041)	(0.091)	(0.055)	(0.073)	(0.071)	(0.055)	(0.105)	(0.117)	(0.072)
22.jobsec	0.018	0.073	0.243	0.211^{***}	-0.041	-0.134*	-0.195**	-0.109	-0.150**	0.367***	0.421^{***}	0.037
	(0.054)	(0.171)	(0.210)	(0.041)	(0.093)	(0.055)	(0.069)	(0.071)	(0.057)	(0.104)	(0.113)	(0.069)
23.jobsec	0.065	0.126	0.309	0.186^{***}	-0.064	-0.118^{*}	0.059	-0.087	-0.124*	0.272^{**}	0.242^{*}	0.207^{**}
	(0.032)	(0.172)	(0.208)	(0.040)	(0.113)	(0.055)	(0.072)	(0.070)	(0.057)	(0.104)	(0.111)	(0.073)
24.jobsec	-0.013	0.047	0.374	0.154^{**}	-0.272	-0.094	-0.229**	-0.181^{*}	-0.080	0.235	0.399^{**}	0.147
	(0.047)	(0.171)	(0.225)	(0.052)	(0.164)	(0.062)	(0.085)	(0.075)	(0.128)	(0.122)	(0.150)	(0.103)
25.jobsec	0.025	0.192	0.223	0.122^{*}	-0.055	-0.092	-0.004	-0.091	-0.066	0.245	0.321^{*}	-0.087
U U	(0.026)	(0.173)	(0.219)	(0.059)	(0.112)	(0.063)	(0.128)	(0.075)	(0.074)	(0.136)	(0.133)	(0.127)
26.jobsec	-0.092		0.168	0.131		. ,	· · · ·	-0.193	0.061	1.142^{***}		-0.104
5	(0.051)		(0.260)	(0.136)				(0.125)	(0.110)	(0.104)		(0.093)
27.jobsec	0.188	0.654^{*}	· /	· /		-0.266**		0.571***	-0.064	0.804***		× /
5	(0.156)	(0.309)				(0.088)		(0.071)	(0.122)	(0.107)		
_cons	3.138***	2.001***	2.021***	2.631***	4.075***	4.966***	1.788^{***}	2.578***	2.287***	2.164***	1.552^{***}	2.058^{***}
-	(0.074)	(0.196)	(0.240)	(0.094)	(0.180)	(0.093)	(0.138)	(0.104)	(0.085)	(0.215)	(0.241)	(0.164)
Ν	42438	1256	1371	9083	1343	2932	2354	2003	2076	1607	1215	1169
R^2	0.402	0.556	0.405	0.493	0.465	0.456	0.454	0.586	0.503	0.507	0.416	0.452

	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.	USA
l.firmsize	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
l 1to 50	-0.093	-0.091	-0.208	-0.072	0.154	0.110	-0.059	-0.020	0.151	-0.117
	(0.194)	(0.126)	(0.147)	(0.119)	(0.165)	(0.178)	(0.084)	(0.079)	(0.211)	(0.202)
51 to 250	0.007	-0.171	-0.202	0.009	0.195	0.126	0.168	-0.026	0.016	-0.049
	(0.207)	(0.147)	(0.138)	(0.124)	(0.154)	(0.177)	(0.100)	(0.075)	(0.209)	(0.206)
251to 1000	0.096	-0.172	-0.157	0.104	0.147	0.251	0.106	0.047	0.062	0.053
	(0.241)	(0.183)	(0.152)	(0.136)	(0.202)	(0.249)	(0.135)	(0.105)	(0.220)	(0.299)
1000+	0.456	-0.387	-0.109	-0.074	0.441	0.533	0.448^{***}	0.070	-0.164	0.266
	(0.266)	(0.234)	(0.208)	(0.147)	(0.245)	(0.286)	(0.114)	(0.106)	(0.216)	(0.247)
educ	0.030^{*}	0.026^{***}	0.025**	0.026^{***}	0.054^{***}	0.057***	0.038***	0.017^{***}	0.023	0.043**
	(0.012)	(0.007)	(0.009)	(0.007)	(0.011)	(0.012)	(0.006)	(0.005)	(0.014)	(0.013)
exper	0.035***	0.024***	0.009*	0.013***	0.018***	0.011	0.016***	0.011***	0.019**	0.012
1	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.007)	(0.005)	(0.003)	(0.006)	(0.007)
expersq	-0.057 ***	-0.039 ***	-0.007	-0.019***	-0.028 ***	-0.018	-0.022*	-0.014 ***	-0.034***	-0.017
1 1	(0.009)	(0.011)	(0.008)	(0.007)	(0.011)	(0.013)	(0.010)	(0.005)	(0.010)	(0.011)
firmeduc2	0.012	0.014	0.021	0.009	-0.000	-0.002	0.008	0.004	0.001	0.015
	(0.015)	(0.010)	(0.011)	(0.008)	(0.013)	(0.013)	(0.007)	(0.006)	(0.016)	(0.015)
irmeduc3	0.010	0.023*	0.026*	0.007	-0.004	-0.004	-0.002	0.007	0.013	0.016
lineauce	(0.016)	(0.011)	(0.010)	(0.008)	(0.012)	(0.013)	(0.008)	(0.006)	(0.016)	(0.015)
ïrmeduc4	0.010	0.028*	0.025*	0.001	0.005	-0.009	0.004	0.006	0.014	0.015
nniedue+	(0.017)	(0.013)	(0.011)	(0.009)	(0.016)	(0.019)	(0.011)	(0.008)	(0.017)	(0.020)
irmeduc5	-0.004	0.056***	0.023	0.015	-0.011	-0.024	-0.014	0.004	0.034*	0.006
millicutes	(0.019)	(0.015)	(0.015)	(0.010)	(0.011)	(0.024)	(0.009)	(0.004)	(0.017)	(0.017)
emale	-0.307***	-0.249***	-0.055**	-0.106^{***}	-0.142^{***}	-0.207***	-0.145***	-0.076***	-0.145***	-0.124**
emale	(0.025)	(0.030)	(0.021)	(0.013)	(0.028)	(0.026)	(0.023)	(0.011)	(0.025)	(0.031)
nigrant	0.317***	-0.050	-0.107***	-0.083***	0.000	0.020)	-0.081	(0.011) -0.047***	-0.045	-0.069
ingrain	(0.057)	(0.088)	(0.032)	(0.023)	(.)	(0.040)	(0.048)	-0.047 (0.014)	(0.043)	(0.040)
) : - 1- 4	0.000	0.000	0.000	0.000		(0.096) 0.000	0.000	(0.014)	0.000	0.000
2.jobtyp					0.000					
	(.)	(.)	(.)	(.)	(.) -0.189***	(.)	(.)	(.)	(.)	(.)
3.jobtyp	-0.191***	-0.183**	-0.073**	-0.040		-0.097	-0.117	-0.143***	-0.087*	-0.046
	(0.042)	(0.062)	(0.026)	(0.022)	(0.054)	(0.063)	(0.073)	(0.020)	(0.042)	(0.042)
1.jobtyp	-0.264***	-0.409***	-0.153***	-0.106***	-0.308***	-0.201***	-0.355***	-0.230***	-0.115**	-0.198**
- • • •	(0.039)	(0.067)	(0.028)	(0.024)	(0.054)	(0.060)	(0.079)	(0.023)	(0.043)	(0.048)
5.jobtyp	-0.376***	-0.301***	-0.306***	-0.220***	-0.517***	-0.312***	-0.380****	-0.360***	-0.386***	-0.469**
	(0.042)	(0.060)	(0.034)	(0.033)	(0.065)	(0.070)	(0.078)	(0.029)	(0.046)	(0.057)
5.jobtyp	-0.461***	-0.588***	-0.297***	-0.234***	-0.585***	-0.511***	-0.469***	-0.318***	-0.429***	-0.521**
	(0.046)	(0.065)	(0.037)	(0.028)	(0.063)	(0.067)	(0.079)	(0.025)	(0.045)	(0.055)
7.jobtyp	-0.370**	-0.254	-0.640***	-0.552	-0.484**	-0.403***	-0.473***	-0.430***	-0.484^{*}	-0.162
	(0.115)	(0.188)	(0.110)	(0.384)	(0.150)	(0.093)	(0.100)	(0.061)	(0.205)	(0.273)
3.jobtyp	-0.467***	-0.464***	-0.328***	-0.251***	-0.510***	-0.367***	-0.385***	-0.366***	-0.331***	-0.356**
	(0.047)	(0.065)	(0.035)	(0.030)	(0.063)	(0.071)	(0.085)	(0.028)	(0.051)	(0.063)
∂.jobtyp	-0.517***	-0.561***	-0.395***	-0.281***	-0.476***	-0.439***	-0.427***	-0.391****	-0.515***	-0.554**
	(0.053)	(0.070)	(0.052)	(0.038)	(0.069)	(0.068)	(0.088)	(0.031)	(0.052)	(0.062)
l0.jobtyp	-0.504***	-0.638***	-0.451***	-0.285***	-0.519***	-0.516***	-0.547***	-0.463***	-0.664***	-0.544**
	(0.084)	(0.066)	(0.046)	(0.047)	(0.065)	(0.071)	(0.082)	(0.034)	(0.049)	(0.093)

7.jobsec	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
8.jobsec	0.353**	0.171	0.411***	0.398***	0.244^{*}	0.115	0.252	0.350***	0.206	0.711****
	(0.123)	(0.132)	(0.087)	(0.054)	(0.110)	(0.122)	(0.161)	(0.075)	(0.363)	(0.213)
9.jobsec	0.227^{*}	-0.086	0.091	0.114^{**}	-0.044	0.094	0.136*	0.049	0.086	0.100
	(0.115)	(0.124)	(0.081)	(0.039)	(0.081)	(0.061)	(0.053)	(0.047)	(0.294)	(0.139)
10.jobsec	0.496^{**}	0.153	0.194	0.163**	0.053	0.242^{**}	0.638***	0.140^{*}	0.009	0.270
	(0.171)	(0.198)	(0.113)	(0.063)	(0.087)	(0.090)	(0.126)	(0.057)	(0.301)	(0.153)
11.jobsec	0.300^{*}	0.095	0.073	0.188	-0.102	0.091	0.225^{**}	0.219^{*}	0.057	0.053
	(0.151)	(0.176)	(0.120)	(0.116)	(0.109)	(0.085)	(0.076)	(0.101)	(0.302)	(0.176)
12.jobsec	0.216	-0.051	0.068	0.091^{*}	0.005	0.130	0.121^{*}	0.163**	0.222	0.273
	(0.120)	(0.128)	(0.085)	(0.038)	(0.087)	(0.073)	(0.050)	(0.050)	(0.299)	(0.147)
13.jobsec	0.141	-0.066	0.063	0.066	-0.117	0.104	0.055	0.068	-0.057	0.018
-	(0.118)	(0.125)	(0.084)	(0.039)	(0.084)	(0.066)	(0.051)	(0.048)	(0.295)	(0.141)
14.jobsec	0.208	-0.059	0.047	0.050	-0.031	0.195**	0.153*	0.063	0.140	0.244
5	(0.121)	(0.134)	(0.093)	(0.045)	(0.090)	(0.069)	(0.059)	(0.052)	(0.296)	(0.161)
15.jobsec	0.133	-0.184	-0.150	-0.047	-0.067	0.029	0.115	-0.029	-0.073	-0.126
5	(0.160)	(0.123)	(0.112)	(0.095)	(0.109)	(0.078)	(0.059)	(0.062)	(0.302)	(0.144)
16.jobsec	0.275^{*}	0.153	0.201*	0.214***	0.105	0.530***	0.253**	0.151**	0.242	0.292^{*}
J	(0.123)	(0.142)	(0.090)	(0.045)	(0.115)	(0.131)	(0.078)	(0.051)	(0.299)	(0.144)
17.jobsec	0.494***	0.265	0.284**	0.148**	0.127	0.233	0.373***	0.185***	0.349	0.202
	(0.139)	(0.141)	(0.087)	(0.052)	(0.148)	(0.122)	(0.089)	(0.055)	(0.301)	(0.147)
18.jobsec	0.198	-0.177	0.277**	0.024	-0.045	-0.077	0.327	0.080	-0.011	0.268
10.00000	(0.127)	(0.175)	(0.090)	(0.090)	(0.115)	(0.099)	(0.205)	(0.058)	(0.316)	(0.194)
19.jobsec	0.308*	0.121	0.187*	0.173***	-0.034	-0.011	0.116	0.147**	0.247	0.263
19.300300	(0.125)	(0.141)	(0.085)	(0.045)	(0.111)	(0.091)	(0.072)	(0.049)	(0.296)	(0.148)
20.jobsec	0.091	-0.212	0.005	0.081	-0.305**	0.085	0.079	0.009	-0.094	-0.007
20.900300	(0.123)	(0.127)	(0.093)	(0.056)	(0.107)	(0.087)	(0.055)	(0.049)	(0.298)	(0.151)
21.jobsec	0.380**	0.121	0.153	0.019	0.082	0.152*	0.279***	-0.006	0.176	0.174
21.j00300	(0.120)	(0.132)	(0.082)	(0.01)	(0.084)	(0.070)	(0.047)	(0.048)	(0.295)	(0.174)
22.jobsec	0.322**	0.034	-0.041	-0.121**	-0.141	-0.121	0.174**	-0.161***	-0.019	-0.240
22.j00sec	(0.124)	(0.130)	(0.041)	(0.039)	(0.080)	(0.068)	(0.053)	(0.047)	(0.296)	(0.143)
23.jobsec	0.236*	-0.153	0.066	-0.021	-0.178*	0.003	0.146**	-0.022	0.010	0.049
23.j00sec	(0.117)	(0.129)	(0.083)	(0.038)	(0.084)	(0.069)	(0.053)	-0.022 (0.047)	(0.295)	(0.141)
24.jobsec	0.175	-0.149	0.062	0.061	-0.166	0.098	0.085	-0.082	-0.128	-0.039
24.J00sec	(0.133)	(0.149)	(0.102)	(0.001)	(0.111)	(0.120)	(0.122)	(0.063)	(0.306)	(0.176)
25 :				0.096		0.085	-0.055	0.025		
25.jobsec	0.046	-0.176	0.120		-0.252				-0.083	0.036
26:1	(0.123)	(0.138)	(0.103)	(0.051)	(0.204)	(0.143)	(0.076)	(0.070)	(0.306)	(0.152)
26.jobsec		-0.482***					-0.174		0.314	0.252
07.1		(0.140)					(0.093)		(0.310)	(0.239)
27.jobsec									0.265	
	· · · · ***	0.101***	0.001***	4.00	0.100***	0 < - 2**	1	1012***	(0.296)	0.0***
_cons	6.611***	9.131***	2.391***	4.897***	2.103***	0.663**	1.720***	4.942***	2.081***	2.361***
	(0.196)	(0.152)	(0.161)	(0.128)	(0.184)	(0.202)	(0.125)	(0.087)	(0.346)	(0.261)
N	1750	1720	1328	1578	1003	1512	1395	1798	1916	1334
R^2	0.497	0.536	0.501	0.484	0.523	0.417	0.540	0.513	0.493	0.525

Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Sample: full-time employees aged 35–54. Numeracy score standardized to std. dev. 1 within each country. Experiencesq divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2 . Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Table A11 and A12. Model 7 Public vs. Private

Table A11 Private sector

1.6	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland	Italy
1.firmsize	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
11to 50	$(.) \\ 0.068^{***}$	(.) 0.113***	(.) 0.003	(.) 0.061**	$(.) \\ 0.088^{*}$	(.) 0.063***	$(.) \\ 0.070^{*}$	(.) 0.059**	(.) 0.037	(.) 0.070	$(.) \\ 0.107^{*}$	$(.) \\ 0.076^{*}$
1110 50	(0.005)	(0.030)	(0.028)	(0.021)	(0.039)	(0.018)	(0.031)	(0.019)	(0.020)	(0.040)	(0.043)	(0.036
51 to 250	0.108***	0.149***	0.040	0.127***	0.071	0.078***	0.095**	0.141***	0.080***	0.185***	0.138**	0.126*
	(0.006)	(0.032)	(0.029)	(0.022)	(0.049)	(0.019)	(0.034)	(0.021)	(0.021)	(0.042)	(0.053)	(0.042
251to 1000	0.170***	0.166***	0.099**	0.218***	0.222***	0.165***	0.195***	0.189***	0.112***	0.274***	0.259***	0.161*
	(0.008)	(0.034)	(0.031)	(0.024)	(0.052)	(0.024)	(0.045)	(0.027)	(0.025)	(0.046)	(0.049)	(0.061
1000 +	0.222***	0.198^{***}	0.091^{*}	0.266^{***}	0.187^{**}	0.172^{***}	0.028	0.239***	0.255***	0.389***	0.256***	0.218^{*}
	(0.016)	(0.039)	(0.039)	(0.031)	(0.067)	(0.025)	(0.085)	(0.037)	(0.031)	(0.048)	(0.064)	(0.060
numscore1	0.056***	0.057***	0.056***	0.065***	0.044*	0.047***	0.073***	0.021*	0.053***	0.076***	0.144***	0.037*
	(0.003)	(0.012)	(0.012)	(0.010)	(0.017)	(0.009)	(0.015)	(0.010)	(0.010)	(0.016)	(0.025)	(0.016
educ	0.030***	0.035***	0.017***	0.019***	0.032***	0.026***	0.018**	0.025***	0.021***	0.014*	0.011	0.030*
	(0.002) 0.015***	(0.005) -0.000	(0.005) 0.008	(0.003) 0.014***	(0.008) 0.015*	(0.004) 0.003	$(0.006) \\ 0.016^*$	(0.004) 0.014^{**}	(0.003) 0.016^{***}	(0.007) 0.011	(0.006) 0.002	(0.006) 0.016^{*}
exper	(0.015)	-0.000 (0.007)	(0.008)	(0.014)	(0.015)	(0.003)	(0.016)	(0.014)	(0.016)	(0.011)	(0.002)	(0.016)
expersq	-0.021***	0.009	-0.009	-0.020**	-0.023	-0.001	-0.030^{*}	(0.004) -0.018 [*]	-0.016	-0.009	0.002	-0.003
experse	(0.004)	(0.00)	(0.012)	(0.007)	(0.014)	(0.007)	(0.013)	(0.007)	(0.009)	(0.012)	(0.016)	(0.013
2.agecoh	0.002	0.015	0.007	0.008	-0.064	0.022	-0.041	-0.092***	-0.008	0.034	0.050	0.007
Lugeron	(0.007)	(0.031)	(0.031)	(0.025)	(0.057)	(0.024)	(0.042)	(0.027)	(0.027)	(0.035)	(0.053)	(0.037
3.agecoh	-0.010	(, , , , , , , , , , , , , , , , , , ,	0.032		-0.092	0.028	-0.198***	-0.044	-0.013	(,	0.078	0.004
-	(0.013)		(0.036)		(0.056)	(0.025)	(0.047)	(0.032)	(0.028)		(0.055)	(0.041
4.agecoh	-0.012	0.019	0.050	-0.009	-0.074	0.008	-0.239***	-0.032	-0.044	-0.014	0.024	0.049
	(0.013)	(0.037)	(0.043)	(0.025)	(0.062)	(0.027)	(0.052)	(0.033)	(0.032)	(0.041)	(0.062)	(0.048
5.agecoh	-0.025	0.020	0.050	-0.023	-0.097	-0.021	-0.230***	-0.096**	-0.028	-0.047	0.080	-0.040
	(0.013)	(0.042)	(0.052)	(0.026)	(0.069)	(0.030)	(0.059)	(0.037)	(0.037)	(0.048)	(0.066)	(0.050
female	-0.141***	-0.120***	-0.062**	-0.172***	-0.146***	-0.093***	-0.344***	-0.155***	-0.047**	-0.100***	-0.070^{*}	-0.098
	(0.017)	(0.026)	(0.020)	(0.017)	(0.036)	(0.014)	(0.027)	(0.018)	(0.018)	(0.028)	(0.034)	(0.028
migrant	-0.067***	-0.098***	-0.038	-0.055**	-0.063	-0.091***	-0.115***	-0.094*	0.033	-0.017	-0.072	-0.034
1 :- 1. ((0.017)	(0.028)	(0.035)	(0.018)	(0.059)	(0.022)	(0.034)	(0.040)	(0.026)	(0.035)	(0.043)	(0.050
2.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3 johtun	(.) -0.083***	(.) -0.034	(.) -0.029	(.) -0.044	(.) -0.067	(.) -0.085**	(.) -0.141**	(.) -0.093**	(.) -0.049	(.) -0.117**	(.) 0.050	(.) -0.138
3.jobtyp	-0.083	(0.034)	(0.029)	(0.028)	(0.103)	(0.030)	(0.051)	(0.031)	(0.034)	(0.042)	(0.074)	(0.128
4.jobtyp	-0.205***	-0.116**	-0.136***	-0.196***	-0.151	-0.182***	-0.258***	-0.256***	-0.249***	-0.298***	-0.093	-0.300
1.jobtyp	(0.013)	(0.043)	(0.039)	(0.027)	(0.089)	(0.031)	(0.053)	(0.031)	(0.029)	(0.050)	(0.079)	(0.120
5.jobtyp	-0.317***	-0.251***	-0.218***	-0.370***	-0.298**	-0.229***	-0.397***	-0.399***	-0.349***	-0.337***	-0.211**	-0.455
5 51	(0.022)	(0.048)	(0.039)	(0.032)	(0.094)	(0.035)	(0.064)	(0.036)	(0.035)	(0.051)	(0.079)	(0.123
6.jobtyp	-0.403***	-0.301****	-0.329***	-0.416***	-0.370***	-0.340***	-0.669***	-0.451***	-0.472***	-0.532***	-0.339***	-0.397
	(0.023)	(0.056)	(0.047)	(0.032)	(0.111)	(0.039)	(0.054)	(0.039)	(0.038)	(0.059)	(0.077)	(0.125
7.jobtyp	-0.372***	-0.343	-0.641**	-0.351***	-0.980***	-0.259***	-0.415***	-0.599***	-0.510***	-0.316**	-0.358*	-0.465
	(0.027)	(0.252)	(0.231)	(0.093)	(0.157)	(0.062)	(0.103)	(0.100)	(0.078)	(0.103)	(0.170)	(0.151
8.jobtyp	-0.318***	-0.296***	-0.294***	-0.238***	-0.278**	-0.278***	-0.304***	-0.407***	-0.332***	-0.455***	-0.143	-0.417
	(0.021)	(0.047)	(0.043)	(0.033)	(0.098)	(0.033)	(0.058)	(0.037)	(0.035)	(0.050)	(0.087)	(0.126
9.jobtyp	-0.395***	-0.344***	-0.362***	-0.366***	-0.354***	-0.353***	-0.439***	-0.446***	-0.417***	-0.543***	-0.303***	-0.455
10 . 17	(0.016)	(0.051)	(0.048)	(0.038)	(0.096)	(0.038)	(0.054)	(0.041)	(0.035)	(0.053)	(0.089)	(0.125
10.jobtyp	-0.485***	-0.404	-0.385	-0.522	-0.440	-0.317***	-0.636***	-0.561	-0.423	-0.638***	-0.289***	-0.493
7.jobsec	(0.030) 0.000	(0.053) 0.000	(0.053) 0.000	(0.035) 0.000	(0.101) 0.000	(0.038) 0.000	(0.061) 0.000	(0.048) 0.000	(0.038) 0.000	(0.070) 0.000	(0.084) 0.000	(0.126 0.000
, .j003ee	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
8.jobsec	0.330***	-0.155	0.684**	0.418***	0.250*	0.147	0.339*	0.060	-0.227*	0.512***	0.383*	-0.040
	(0.039)	(0.224)	(0.214)	(0.065)	(0.106)	(0.105)	(0.149)	(0.122)	(0.111)	(0.151)	(0.185)	(0.087
9.jobsec	0.094**	0.033	0.510**	0.117*	0.084	0.057	-0.011	0.085	-0.018	0.562***	0.305**	0.193*
	(0.032)	(0.201)	(0.173)	(0.046)	(0.093)	(0.060)	(0.071)	(0.117)	(0.069)	(0.102)	(0.108)	(0.074
10.jobsec	0.245***	0.151	0.424^{*}	0.465***	0.229	0.068	0.303*	0.287^{*}	0.071	0.510***	0.373	0.184*
-	(0.054)	(0.219)	(0.179)	(0.115)	(0.124)	(0.072)	(0.127)	(0.142)	(0.093)	(0.128)	(0.201)	(0.087
11.jobsec	0.111^{**}	-0.182	0.465**	0.040	-0.006	0.038	0.294**	0.072	0.023	0.432**	0.398**	0.219*
	(0.033)	(0.213)	(0.176)	(0.122)	(0.110)	(0.071)	(0.110)	(0.129)	(0.094)	(0.137)	(0.130)	(0.098
12.jobsec	0.160***	0.088	0.433*	0.237***	0.146	0.083	0.223**	0.180	-0.007	0.468^{***}	0.294^{*}	0.098
	(0.029)	(0.202)	(0.176)	(0.052)	(0.101)	(0.061)	(0.082)	(0.117)	(0.071)	(0.105)	(0.137)	(0.089
13.jobsec	0.020	-0.042	0.490**	0.008	-0.006	0.020	0.052	0.131	-0.044	0.444***	0.329**	0.104
14 * 1	(0.029)	(0.202)	(0.173)	(0.046)	(0.095)	(0.062)	(0.076)	(0.118)	(0.070)	(0.103)	(0.110)	(0.072
14.jobsec	0.105^{***}	-0.069	0.511^{**}	0.076	0.135	-0.014	0.170^{*}	0.089	-0.031	0.354**	0.199	0.158
15 johana	(0.025)	(0.204)	(0.175) 0.455*	(0.053) 0.102*	(0.131)	(0.067)	(0.080)	(0.121)	(0.077)	(0.110)	(0.158)	(0.093
15.jobsec	-0.087* (0.037)	-0.151	0.455^{*}	-0.103^{*}	-0.157	0.004	0.013	0.094	-0.064	0.153	0.199	0.088
	(0.05/)	(0.205)	(0.181)	(0.052)	(0.118)	(0.069)	(0.102)	(0.123)	(0.081)	(0.141)	(0.115)	(0.098
16 jobsec		0 222	0 52/**	0 101***	0.204	0.060	0.260**	0 152	0.025	0 525***	0 200**	0 177
16.jobsec	0.178 ^{***} (0.025)	0.233 (0.203)	0.534 ^{**} (0.181)	0.191*** (0.055)	0.204 (0.112)	0.060 (0.065)	0.269** (0.096)	0.152 (0.120)	0.025 (0.079)	0.525*** (0.112)	0.309 ^{**} (0.118)	0.172 (0.103

R^2	0.410	0.587	0.457	0.500	0.478	0.488	0.454	0.589	0.537	0.548	0.471	0.472
Ν	42424	824	889	5249	893	1628	1493	1176	1434	1126	737	819
	(0.069)	(0.225)	(0.202)	(0.085)	(0.183)	(0.108)	(0.138)	(0.138)	(0.098)	(0.183)	(0.177)	(0.171
_cons	3.117***	2.274^{***}	2.107^{***}	2.750^{***}	4.328***	4.976^{***}	1.604***	2.584^{***}	2.326***	2.053***	2.286^{***}	1.942^{*}
	(0.147)								(0.076)			
27.jobsec	0.198								-0.256***			
5	(0.050)		(0.225)	(0.194)				(0.150)	(0.139)	(0.113)		(0.097
26.jobsec	-0.077		0.378	0.118	. ,	. ,		-0.064	0.119	1.406***		-0.148
5	(0.027)	(0.214)	(0.198)	(0.088)	(0.123)	(0.082)	(0.197)	(0.135)	(0.086)	(0.137)	(0.163)	(0.155
25.jobsec	0.016	0.095	0.403*	0.130	-0.096	-0.038	-0.026	0.075	0.012	0.293*	0.221	-0.083
	(0.046)	(0.187)	(0.229)	(0.089)	(0.196)	(0.075)	(0.316)	(0.133)	(0.184)	(0.136)	(0.184)	(0.101
24.jobsec	-0.018	-0.028	0.712 ^{**}	0.060	-0.132	-0.068	-0.567	-0.041	0.007	0.249	0.450^{*}	0.221
5	(0.034)	(0.208)	(0.174)	(0.053)	(0.127)	(0.065)	(0.088)	(0.121)	(0.072)	(0.110)	(0.116)	(0.085
23.jobsec	0.068	0.038	0.499* ^{**}	0.159**	-0.219	-0.044	0.067	0.068	-0.112	0.400^{***}	0.267^{*}	0.093
	(0.056)	(0.211)	(0.235)	(0.055)	(0.191)	(0.069)	(0.146)	(0.134)	(0.089)	(0.144)	(0.140)	(0.122
22.jobsec	0.016	-0.156	0.505^{*}	0.037	-0.221	-0.119	-0.039	0.036	-0.184*	0.513***	0.214	0.201
	(0.049)	(0.213)	(0.186)	(0.147)	(0.125)	(0.090)	(0.084)		(0.085)	(0.113)	(0.114)	(0.106
21.jobsec	0.167**	0.052	0.631***	0.455**	-0.078	0.016	0.677***		-0.032	0.350**	0.455***	0.157
-	(0.024)	(0.218)	(0.177)	(0.059)	(0.177)	(0.070)	(0.101)	(0.119)	(0.072)	(0.107)	(0.117)	(0.086
20.jobsec	-0.003	-0.160	0.508**	0.052	-0.065	0.029	0.046	0.051	-0.103	0.344**	0.318**	-0.026
U U	(0.031)	(0.206)	(0.175)	(0.051)	(0.120)	(0.062)	(0.107)	(0.119)	(0.078)	(0.112)	(0.113)	(0.089
19.jobsec	0.150^{***}	-0.025	0.469^{**}	0.229^{***}	0.083	0.113	0.136	0.062	0.010	0.440^{***}	0.521^{***}	0.124
	(0.046)	(0.208)	(0.175)	(0.081)	(0.183)	(0.072)	(0.122)	(0.154)	(0.107)	(0.135)	(0.200)	(0.116
18.jobsec	0.105^{*}	0.324	0.663***	0.034	0.142	0.094	-0.048	0.042	-0.065	0.392**	0.642^{**}	0.117
	(0.030)	(0.202)	(0.175)	(0.049)	(0.131)	(0.063)	(0.097)	(0.120)	(0.075)	(0.124)	(0.118)	(0.106

	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.	USA
1.firmsize	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
11to 50	0.055	0.068^{*}	0.070^{*}	0.056^{*}	0.143***	0.124**	0.005	0.047^{*}	0.149***	0.090
	(0.033)	(0.034)	(0.030)	(0.024)	(0.043)	(0.041)	(0.029)	(0.020)	(0.044)	(0.050)
51 to 250	0.118***	0.098**	0.122***	0.136***	0.167***	0.132**	0.161***	0.074^{***}	0.135**	0.187^{***}
	(0.035)	(0.038)	(0.032)	(0.027)	(0.042)	(0.044)	(0.037)	(0.021)	(0.044)	(0.049)
251to 1000	0.254***	0.148**	0.176***	0.144***	0.240***	0.151**	0.175***	0.151***	0.212***	0.268***
1000	(0.042)	(0.055)	(0.035)	(0.034)	(0.061)	(0.048)	(0.047)	(0.026)	(0.048)	(0.060)
1000 +	0.391***	0.398***	0.211***	0.157***	0.358***	0.239***	0.234***	0.183***	0.270***	0.294***
	(0.045)	(0.060)	(0.052)	(0.037)	(0.074)	(0.060)	(0.063)	(0.030)	(0.054)	(0.060)
numscore1	0.058***	0.059***	0.060***	0.041***	0.060**	0.077***	0.054**	0.042***	0.087***	0.064**
	(0.014) 0.030^{***}	(0.015) 0.030***	(0.013) 0.034***	(0.010) 0.031***	(0.019) 0.046^{***}	(0.018) 0.046 ^{***}	(0.018) 0.026***	(0.011) 0.016^{***}	(0.016) 0.034***	(0.021) 0.039***
educ	(0.030)	(0.030)	(0.034 (0.006)	(0.031)	0.046 (0.009)	(0.046)	(0.026)	(0.016)	(0.034 (0.007)	(0.039)
	0.028***	0.026***	-0.005	0.003)	(0.009) 0.017^*	0.008)	0.003)	(0.004) 0.009*	0.013	0.008
exper	(0.028)	(0.026)	-0.005 (0.006)	(0.004)	(0.017)	(0.003)	(0.008)	(0.009)	(0.013)	(0.001)
avpora	-0.045***	-0.053***	(0.008) 0.017	-0.007	-0.025	-0.013	-0.003	-0.011	-0.017	0.009)
expersq	(0.010)	-0.033 (0.012)	(0.017)	-0.007 (0.009)	-0.025 (0.015)	(0.013)	(0.012)	(0.007)	-0.017 (0.015)	(0.002)
2.agecoh	0.039	-0.022	0.129**	-0.006	0.054	0.020)	0.054	0.003	0.047	0.030
2.agecon	(0.039)	(0.038)	(0.040)	(0.027)	(0.054)	(0.048)	(0.034)	(0.026)	(0.047)	(0.030
3.agecoh	0.003	-0.053	0.116**	0.015	-0.011	0.035	0.057	0.043	-0.005	(0.047)
5.agecon	(0.038)	(0.045)	(0.041)	(0.030)	(0.056)	(0.064)	(0.041)	(0.028)	(0.056)	
4.agecoh	0.048	-0.034	0.077	0.057	-0.018	0.043	0.033	0.024	-0.066	0.054
nugecon	(0.046)	(0.043)	(0.041)	(0.032)	(0.064)	(0.063)	(0.042)	(0.030)	(0.057)	(0.051)
5.agecoh	0.036	-0.002	0.076	0.033	-0.040	0.058	-0.035	0.015	-0.046	0.038
8	(0.044)	(0.048)	(0.049)	(0.038)	(0.063)	(0.073)	(0.047)	(0.034)	(0.058)	(0.063)
female	-0.313***	-0.286***	-0.051	-0.097***	-0.137***	-0.213***	-0.165***	-0.084***	-0.133***	-0.107**
	(0.031)	(0.035)	(0.031)	(0.019)	(0.038)	(0.031)	(0.032)	(0.016)	(0.034)	(0.041)
migrant	0.348***	-0.086	-0.103**	-0.065*	0.000	-0.011	-0.051	-0.042*	-0.028	-0.039
0	(0.049)	(0.070)	(0.039)	(0.031)	(.)	(0.134)	(0.048)	(0.020)	(0.044)	(0.046)
2.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
3.jobtyp	-0.154**	-0.197**	-0.103**	-0.041	-0.207*	-0.060	-0.149	-0.110***	-0.088	0.006
	(0.049)	(0.070)	(0.037)	(0.030)	(0.086)	(0.084)	(0.100)	(0.028)	(0.052)	(0.053)
4.jobtyp	-0.245***	-0.438***	-0.136***	-0.086**	-0.272**	-0.207**	-0.369***	-0.193***	-0.030	-0.173**
	(0.043)	(0.077)	(0.037)	(0.030)	(0.084)	(0.074)	(0.101)	(0.030)	(0.059)	(0.061)
5.jobtyp	-0.380***	-0.311***	-0.332***	-0.236***	-0.612***	-0.287***	-0.358***	-0.327***	-0.309***	-0.536**
	(0.047)	(0.067)	(0.043)	(0.039)	(0.091)	(0.084)	(0.100)	(0.037)	(0.059)	(0.074)
6.jobtyp	-0.467***	-0.588***	-0.303***	-0.228***	-0.684***	-0.565***	-0.576***	-0.333****	-0.421***	-0.551**
	(0.051)	(0.072)	(0.046)	(0.041)	(0.087)	(0.082)	(0.101)	(0.037)	(0.059)	(0.066)
7.jobtyp	-0.252*	-0.296	-0.704*	-0.528	-0.515**	-0.414***	-0.632***	-0.337***	-0.736**	-0.204
~	(0.116)	(0.218)	(0.326)	(0.381)	(0.171)	(0.110)	(0.126)	(0.072)	(0.225)	(0.308)
8.jobtyp	-0.446***	-0.458***	-0.332***	-0.230***	-0.522***	-0.331***	-0.431***	-0.327***	-0.309***	-0.369**
o	(0.048)	(0.070)	(0.040)	(0.035)	(0.082)	(0.084)	(0.105)	(0.035)	(0.055)	(0.068)
9.jobtyp	-0.472***	-0.552***	-0.379***	-0.248***	-0.478***	-0.393***	-0.462***	-0.337***	-0.450***	-0.565**

10 1 1	(0.053)	(0.074)	(0.060)	(0.043)	(0.092)	(0.082)	(0.109)	(0.037)	(0.055)	(0.076)
10.jobtyp	-0.478***	-0.610***	-0.374***	-0.304***	-0.518***	-0.477***	-0.603***	-0.422***	-0.556***	-0.499***
7 :	(0.091)	(0.070)	(0.060) 0.000	(0.052)	(0.091)	(0.090)	(0.105)	(0.046) 0.000	(0.057)	(0.103)
7.jobsec	0.000	0.000		0.000	0.000	0.000	0.000	(.)	0.000	0.000
8.jobsec	(.) 0.476 ^{***}	(.) -0.004	(.) 0.446 ^{***}	(.) 0.359***	(.) 0.151	(.) 0.082	(.) 0.239	(.) 0.329***	(.) 0.097	(.) 0.803 ^{**}
a.jobsec	(0.124)	-0.004 (0.150)	(0.098)	(0.062)	(0.156)	(0.130)	(0.160)	(0.082)	(0.350)	(0.245)
9.jobsec	0.305**	-0.253	0.098	0.099*	-0.093	0.061	0.141*	0.020	0.158	0.245)
9.300300	(0.110)	(0.140)	(0.087)	(0.045)	(0.096)	(0.077)	(0.055)	(0.054)	(0.287)	(0.160)
10.jobsec	0.547***	-0.370	0.198	0.140	-0.037	0.243*	0.632***	0.147	0.088	0.371*
10.900.000	(0.164)	(0.331)	(0.121)	(0.075)	(0.109)	(0.100)	(0.130)	(0.076)	(0.297)	(0.184)
11.jobsec	0.443**	0.003	0.037	0.146	-0.011	0.020	0.243**	0.051	0.138	0.023
	(0.167)	(0.205)	(0.124)	(0.110)	(0.177)	(0.105)	(0.077)	(0.072)	(0.300)	(0.204)
12.jobsec	0.309**	-0.225	0.067	0.083	-0.024	0.131	0.111*	0.158**	0.263	0.389*
	(0.115)	(0.143)	(0.090)	(0.045)	(0.097)	(0.087)	(0.050)	(0.056)	(0.292)	(0.167)
13.jobsec	0.243*	-0.241	0.059	0.072	-0.113	0.135	0.096	0.065	0.018	0.123
-	(0.112)	(0.141)	(0.089)	(0.045)	(0.100)	(0.081)	(0.049)	(0.056)	(0.288)	(0.161)
14.jobsec	0.245^{*}	-0.328*	0.001	0.032	-0.117	0.191^{*}	0.093	0.035	0.187	0.347
	(0.115)	(0.151)	(0.096)	(0.056)	(0.111)	(0.095)	(0.064)	(0.060)	(0.290)	(0.190)
15.jobsec	0.253	-0.326*	-0.173	-0.064	-0.110	0.096	0.184^{**}	0.001	0.068	0.002
	(0.159)	(0.141)	(0.115)	(0.093)	(0.126)	(0.095)	(0.059)	(0.068)	(0.294)	(0.166)
16.jobsec	0.335**	-0.028	0.179	0.176^{***}	0.017	0.602^{***}	0.222^{**}	0.117^{*}	0.276	0.395^{*}
	(0.118)	(0.158)	(0.097)	(0.051)	(0.139)	(0.135)	(0.083)	(0.059)	(0.292)	(0.164)
17.jobsec	0.577^{***}	0.101	0.253**	0.112	0.048	0.242	0.366***	0.159^{*}	0.371	0.336*
	(0.137)	(0.162)	(0.093)	(0.060)	(0.168)	(0.149)	(0.087)	(0.062)	(0.294)	(0.167)
18.jobsec	0.255*	-0.341	0.279**	0.025	-0.122	-0.039	0.308	0.114	-0.025	0.361
40.1.1	(0.118)	(0.193)	(0.107)	(0.099)	(0.134)	(0.143)	(0.202)	(0.066)	(0.308)	(0.214)
19.jobsec	0.355**	-0.001	0.167	0.174***	-0.084	0.043	0.052	0.132*	0.275	0.379*
20 1	(0.122)	(0.159)	(0.092)	(0.051)	(0.135)	(0.130)	(0.089)	(0.057)	(0.291)	(0.171)
20.jobsec	0.194	-0.400**	0.021	0.133*	-0.271*	0.152	0.125*	0.019	-0.032	0.124
21 :	(0.118) 0.682^{***}	(0.142)	(0.099) 0.085	(0.067)	(0.126) -0.384**	(0.110) 0.075	(0.056) -0.091	(0.060)	(0.290)	(0.174) 0.417
21.jobsec	(0.130)	0.033 (0.145)	(0.119)			(0.075)	-0.091 (0.129)		0.147 (0.295)	(0.267)
22.jobsec	0.483***	-0.120	0.121	-0.063	(0.123) -0.096	(0.099) 0.160	(0.129) 0.201^*	-0.152*	0.100	-0.187
22.J00sec	(0.143)	(0.153)	(0.121)	(0.066)	(0.216)	(0.247)	(0.084)	(0.068)	(0.302)	-0.187 (0.190)
23.jobsec	0.320**	-0.351^*	0.134)	-0.015	-0.062	0.123	0.061	0.077	0.011	0.143
25.j003ee	(0.113)	(0.145)	(0.092)	(0.051)	(0.108)	(0.092)	(0.001)	(0.061)	(0.292)	(0.163)
24.jobsec	0.289*	-0.513**	-0.118	0.018	0.053	0.304	0.070	-0.042	-0.035	0.165
21.900300	(0.126)	(0.181)	(0.197)	(0.082)	(0.281)	(0.165)	(0.121)	(0.102)	(0.303)	(0.207)
25.jobsec	0.076	-0.274	0.180	0.139*	0.087	0.039	0.052	0.068	0.173	0.192
23.300300	(0.120)	(0.156)	(0.122)	(0.064)	(0.139)	(0.153)	(0.080)	(0.138)	(0.323)	(0.185)
26.jobsec	()	-0.551**	()	()	()	()	-0.043	()	0.420	0.395
		(0.171)					(0.094)		(0.293)	(0.250)
_cons	6.582***	9.305***	2.371***	4.918***	2.262***	0.830***	1.946***	4.921***	1.853***	2.383***
							(0.139)	(0.100)		
	(0.157)	(0.173)	(0.150)	(0.111)	(0.194)	(0.208)	(0.139)	(0.100)	(0.327)	(0.228)
$\frac{N}{R^2}$	(0.157) 1419	(0.173) 1339	(0.150) 830	923	625	994	926	978	1064	(0.228) 863

Public sector

Table A12 Public sector

	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland	Italy
1.firmsize	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
11to 50	0.044***	0.037	-0.049	0.094**	0.064	0.062^{*}	0.057	0.078***	0.041	-0.123	0.210^{*}	0.003
	(0.011)	(0.048)	(0.051)	(0.035)	(0.043)	(0.025)	(0.040)	(0.022)	(0.042)	(0.064)	(0.095)	(0.066
51 to 250	0.072^{***}	0.091	-0.006	0.110^{**}	0.189***	0.073**	0.131**	0.113***	0.086^*	-0.006	0.259^{**}	0.015
	(0.012)	(0.050)	(0.049)	(0.035)	(0.043)	(0.027)	(0.041)	(0.024)	(0.041)	(0.058)	(0.090)	(0.064
251to 1000	0.090^{***}	0.127^{*}	0.039	0.134***	0.011	0.138***	0.160^{**}	0.125^{***}	0.073	-0.036	0.253^{*}	-0.00
	(0.012)	(0.054)	(0.054)	(0.035)	(0.056)	(0.032)	(0.052)	(0.032)	(0.042)	(0.063)	(0.102)	(0.07
1000+	0.126***	0.070	0.016	0.147***	0.233**	0.113***	0.228***	0.150***	0.142**	0.006	0.125	0.082
	(0.018)	(0.067)	(0.063)	(0.036)	(0.090)	(0.032)	(0.068)	(0.034)	(0.050)	(0.077)	(0.111)	(0.07
numscore1	0.042***	0.047^{*}	0.071***	0.051***	0.011	0.031***	0.047***	0.022^{*}	0.041**	0.043	0.052	0.055
	(0.003)	(0.020)	(0.017)	(0.011)	(0.025)	(0.008)	(0.014)	(0.010)	(0.014)	(0.023)	(0.033)	(0.02
educ	0.036***	0.051***	0.043***	0.033***	0.030***	0.037***	0.038***	0.024***	0.024***	0.045***	0.061***	-0.002
educ	(0.003)	(0.008)	(0.007)	(0.004)	(0.008)	(0.004)	(0.006)	(0.004)	(0.005)	(0.010)	(0.010)	(0.01
ovpor	0.015***	0.014	0.009	0.006	0.027*	0.000	0.012	0.012**	0.021**	(0.010) 0.024^*	0.037*	-0.00
exper												
	(0.003)	(0.014)	(0.011)	(0.005)	(0.012)	(0.003)	(0.008)	(0.005)	(0.007)	(0.010)	(0.015)	(0.00
expersq	-0.020****	-0.005	-0.001	-0.007	-0.043*	0.005	-0.021	-0.023**	-0.028*	-0.031	-0.051	0.012
	(0.005)	(0.028)	(0.018)	(0.010)	(0.021)	(0.006)	(0.014)	(0.009)	(0.014)	(0.017)	(0.028)	(0.01
1.agecoh	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2.agecoh	-0.012	0.079	0.046	0.012	-0.019	0.011	-0.105*	0.003	0.013	-0.100	-0.009	0.037
	(0.010)	(0.060)	(0.056)	(0.029)	(0.063)	(0.027)	(0.047)	(0.035)	(0.040)	(0.065)	(0.070)	(0.07
3.agecoh	-0.009		0.021		-0.078	0.049	-0.118^{*}	-0.021	-0.017		0.059	0.010
-	(0.014)		(0.064)		(0.072)	(0.028)	(0.053)	(0.036)	(0.043)		(0.089)	(0.06
4.agecoh	-0.016	0.017	0.078	0.029	-0.058	0.013	-0.061	-0.024	0.049	-0.087	-0.019	0.044
U	(0.012)	(0.060)	(0.065)	(0.030)	(0.077)	(0.029)	(0.057)	(0.040)	(0.043)	(0.072)	(0.093)	(0.06
5.agecoh	-0.013	0.066	0.066	0.043	-0.069	0.046	-0.151*	0.021	0.109*	-0.133	-0.125	0.021
Sugeeon	(0.016)	(0.066)	(0.074)	(0.031)	(0.096)	(0.030)	(0.066)	(0.021)	(0.046)	(0.074)	(0.083)	(0.07
female	-0.097***	-0.087*	-0.056	-0.102***	-0.102^*	-0.030	-0.150***	-0.119***	-0.085***	-0.108**	-0.150**	-0.13
remaie	(0.011)	(0.035)	(0.032)	(0.019)	(0.047)	(0.018)	(0.035)	(0.020)	(0.022)	(0.036)	(0.055)	(0.04
mignant					. ,					. ,	· · · ·	
migrant	-0.019	-0.094	0.103	0.009	0.073	-0.017	-0.080*	-0.039	0.002	-0.040	-0.044	-0.12
	(0.014)	(0.051)	(0.076)	(0.023)	(0.103)	(0.023)	(0.034)	(0.056)	(0.039)	(0.067)	(0.066)	(0.14
2.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
3.jobtyp	-0.080***	-0.017	-0.011	-0.006	-0.019	-0.117***	-0.147**	-0.009	-0.079	-0.052	-0.030	-0.12
	(0.020)	(0.070)	(0.066)	(0.033)	(0.069)	(0.027)	(0.050)	(0.042)	(0.046)	(0.052)	(0.092)	(0.19
4.jobtyp	-0.215***	-0.107	-0.071	-0.174***	-0.169*	-0.110***	-0.302***	-0.231***	-0.243***	-0.184**	-0.235*	-0.44
	(0.017)	(0.071)	(0.075)	(0.037)	(0.072)	(0.032)	(0.059)	(0.044)	(0.047)	(0.055)	(0.103)	(0.20)
5.jobtyp	-0.322***	-0.268**	-0.137	-0.289***	-0.139	-0.141***	-0.409***	-0.291***	-0.344***	-0.202^{*}	-0.377^{*}	-0.50
5 51	(0.023)	(0.083)	(0.077)	(0.041)	(0.072)	(0.039)	(0.072)	(0.048)	(0.050)	(0.080)	(0.155)	(0.20
6.jobtyp	-0.338***	-0.301***	-0.064	-0.353***	-0.327***	-0.243***	-0.583***	-0.345***	-0.275***	-0.221**	-0.375***	-0.51
JJF	(0.028)	(0.082)	(0.080)	(0.044)	(0.079)	(0.035)	(0.062)	(0.050)	(0.055)	(0.077)	(0.110)	(0.21
7.jobtyp	-0.376***	-0.193*	(0.000)	0.055	-0.288	-0.241***	-0.442***	-0.475***	-0.409***	-0.951***	-0.266	-0.28
7.Jobtyp	(0.042)	(0.091)		(0.188)	(0.189)	(0.056)	(0.114)	(0.102)	(0.062)	(0.221)	(0.281)	(0.22)
8 johtyp	-0.298***	-0.294***	-0.153	-0.120^{*}	-0.116	(0.030) -0.174 [*]	(0.114) -0.436 ^{***}	(0.102) -0.503***	-0.431***	-0.323**	-0.380^{**}	-0.64
8.jobtyp												
0:-1-	(0.032)	(0.083)	(0.080)	(0.058)	(0.150)	(0.077)	(0.088) 0.425***	(0.061)	(0.064)	(0.100)	(0.132)	(0.23
9.jobtyp	-0.351***	-0.351***	-0.266**	-0.311***	-0.135	-0.169	-0.435***	-0.300***	-0.426***	-0.360***	-0.261	-0.38
10 1 1	(0.025)	(0.088)	(0.099)	(0.051)	(0.092)	(0.090)	(0.098)	(0.075)	(0.074)	(0.090)	(0.160)	(0.23
10.jobtyp	-0.469***	-0.352***	-0.300****	-0.453***	-0.572***	-0.260***	-0.796***	-0.437***	-0.362***	-0.395*	-0.270*	-0.63
	(0.042)	(0.088)	(0.084)	(0.051)	(0.088)	(0.039)	(0.066)	(0.056)	(0.064)	(0.169)	(0.113)	(0.20
7.jobsec	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
8.jobsec	0.357***	0.241		0.163		0.045	0.136	0.209^{*}	-0.140	-0.540^{*}		0.730
	(0.060)	(0.237)		(0.177)		(0.060)	(0.139)	(0.083)	(0.074)	(0.232)		(0.12
9.jobsec	-0.002	0.509^{*}	-0.054	0.059	0.421^{*}	0.030	-0.386**	0.059	0.009	-0.370	-0.087	0.238
	(0.062)	(0.216)	(0.124)	(0.112)	(0.197)	(0.156)	(0.143)	(0.088)	(0.057)	(0.229)	(0.443)	(0.13
10.jobsec	0.172*	0.644**	-0.343	0.425***	0.301	0.086	-0.303**	-0.088	0.070	0.028	0.313	0.658
3	(0.066)	(0.219)	(0.192)	(0.086)	(0.255)	(0.093)	(0.102)	(0.082)	(0.145)	(0.245)	(0.446)	(0.40
11.jobsec	0.046	0.029	0.271*	0.116	0.214	-0.052	-0.214	-0.140	0.130	0.003	()	0.469
- 1.900000	(0.055)	(0.221)	(0.110)	(0.126)	(0.171)	(0.155)	(0.157)	(0.094)	(0.120)	(0.227)		(0.16
12.jobsec	0.083	0.523*	(0.110)	(0.120) 0.275^*	0.171)	-0.049	-0.212	-0.030	0.080	-0.192	0.503	0.488
12.JODSeC												
12:-1	(0.053)	(0.218)	0.257*	(0.117)	(0.182)	(0.059)	(0.134)	(0.103)	(0.170)	(0.236)	(0.421)	(0.16
13.jobsec	-0.135	0.542	-0.357*	-0.225	0.022	-0.135	-0.306*	-0.119	-0.418***	-0.489*	0.707	0.190
	(0.092)	(0.277)	(0.147)	(0.117)	(0.190)	(0.204)	(0.150)	(0.074)	(0.064)	(0.215)	(0.497)	(0.14
	0.080	0.565^{**}	-0.068	0.173^{*}	0.384^{*}	0.007	-0.249*	-0.108	0.019	-0.187	0.389	0.295
14.jobsec												
14.jobsec	(0.055) -0.133	(0.217) 0.322	(0.081) -0.344***	(0.081) -0.268*	(0.173)	(0.067) -0.149*	(0.102)	(0.087)	(0.063) -0.211	(0.228)	(0.423) 0.079	(0.110

	(0.072)	(0.264)	(0.085)	(0.110)	(0.171)	(0.061)	(0.137)	(0.087)	(0.194)		(0.427)	
16.jobsec	0.072	0.738**	-0.013	0.270**	0.540**	0.044	-0.260	-0.221	-0.058	0.115	0.316	0.637***
10.300300	(0.059)	(0.238)	(0.094)	(0.097)	(0.177)	(0.164)	(0.232)	(0.116)	(0.104)	(0.248)	(0.444)	(0.124)
17.jobsec	0.112	0.798***	-0.052	0.171*	0.094	0.223***	-0.178	0.022	0.006	-0.018	0.362	0.531***
17.j00sec	(0.059)	(0.230)	(0.094)	(0.086)	(0.254)	(0.223)	(0.168)	(0.022)	(0.056)	(0.216)	(0.457)	(0.129)
18.jobsec	0.096	(0.230) 0.657*	(0.094)	-0.002	(0.234)	0.047	-0.316^*	-0.202^*	-0.026	-0.222	(0.437)	(0.129)
18. jubsec	(0.090)	(0.301)		(0.120)		(0.102)	(0.146)	(0.081)	(0.090)	(0.222)		
19.jobsec	0.047	0.338	0.183	-0.045	0.269	(0.102) -0.071	-0.483^{***}	-0.098	-0.135	-0.136	0.736	0.650**
19.j00sec	(0.059)	(0.227)	(0.123)	(0.152)	(0.180)	(0.062)		(0.080)	(0.081)	(0.219)	(0.435)	
20 inhana	(0.039) -0.103 [*]	(0.227) 0.162	-0.103	0.009	(0.180) 0.147	(0.062)	(0.126) -0.052	-0.143	-0.067	-0.194	(0.455) 0.042	(0.232) 0.503***
20.jobsec												
01 :	(0.049) 0.047	(0.230)	(0.090)	(0.096)	(0.221)	(0.069)	(0.287)	(0.087)	(0.125)	(0.219)	(0.486)	(0.115)
21.jobsec		0.426*	-0.047	0.235**	0.351*	-0.051	-0.219**	-0.148	-0.111**	-0.174	0.258	0.487***
22 · 1	(0.048)	(0.213)	(0.064)	(0.078)	(0.162)	(0.054)	(0.078)	(0.077)	(0.040)	(0.213)	(0.413)	(0.089)
22.jobsec	-0.111	0.326	-0.189*	0.088	0.180	-0.104	-0.561***	-0.241**	-0.175***	-0.186	0.263	0.263*
	(0.054)	(0.218)	(0.076)	(0.079)	(0.166)	(0.054)	(0.080)	(0.078)	(0.050)	(0.212)	(0.415)	(0.105)
23.jobsec	-0.043	0.357	-0.127	0.099	0.241	-0.128*	-0.316***	-0.198**	-0.160***	-0.244	0.178	0.562***
	(0.049)	(0.217)	(0.077)	(0.079)	(0.182)	(0.055)	(0.083)	(0.076)	(0.045)	(0.215)	(0.417)	(0.099)
24.jobsec	-0.116	0.073	-0.171	0.110	0.133	-0.093	-0.542***	-0.332***	-0.054	-0.157	0.263	0.507***
	(0.057)	(0.218)	(0.127)	(0.088)	(0.171)	(0.065)	(0.083)	(0.088)	(0.079)	(0.222)	(0.439)	(0.132)
25.jobsec	-0.118	0.390	-0.371***	0.180	0.023	-0.139*	-0.416*	-0.282***	-0.125	-0.022	0.464	0.073
	(0.062)	(0.227)	(0.082)	(0.132)	(0.177)	(0.066)	(0.209)	(0.085)	(0.187)	(0.248)	(0.454)	(0.087)
26.jobsec	-0.512**			0.051								
	(0.165)			(0.088)								
27.jobsec	0.348***	0.865^{**}						0.535***	0.053	0.309		
	(0.081)	(0.307)						(0.079)	(0.061)	(0.217)		
_cons	3.007***	1.390***	2.216^{***}	2.679^{***}	3.851***	4.763***	1.559***	2.706^{***}	2.219***	2.304***	1.354**	2.501^{***}
	(0.097)	(0.316)	(0.174)	(0.126)	(0.254)	(0.097)	(0.156)	(0.134)	(0.135)	(0.290)	(0.478)	(0.295)
Ν	14517	393	431	3416	424	1248	819	772	590	402	452	345
R^2	0.361	0.584	0.443	0.448	0.591	0.446	0.595	0.646	0.519	0.504	0.455	0.433

	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.	USA
1.firmsize	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
11to 50	-0.082	-0.002	0.052	-0.011	0.113	0.013	-0.022	0.024	-0.016	0.102
	(0.135)	(0.110)	(0.056)	(0.041)	(0.071)	(0.047)	(0.049)	(0.017)	(0.070)	(0.085)
51 to 250	0.053	-0.007	0.127**	0.013	0.062	-0.001	0.015	0.048^{**}	-0.005	0.072
	(0.141)	(0.113)	(0.048)	(0.043)	(0.070)	(0.052)	(0.051)	(0.018)	(0.073)	(0.078)
251to 1000	-0.066	0.063	0.141**	0.010	0.084	0.129	0.016	0.099* ^{***}	0.036	0.140
	(0.146)	(0.116)	(0.051)	(0.045)	(0.080)	(0.080)	(0.059)	(0.026)	(0.077)	(0.089)
1000+	-0.017	0.180	0.141**	0.088	0.096	0.112	0.095	0.053*	0.086	0.268**
	(0.148)	(0.125)	(0.053)	(0.045)	(0.096)	(0.093)	(0.064)	(0.026)	(0.072)	(0.099)
numscore1	0.098**	0.002	0.039*	0.035**	0.035	0.076**	0.049*	0.024*	0.074***	0.029
	(0.037)	(0.034)	(0.018)	(0.013)	(0.021)	(0.025)	(0.024)	(0.010)	(0.019)	(0.038)
educ	0.023	0.043***	0.037***	0.029***	0.054***	0.052***	0.044***	0.023***	0.023**	0.075**
cuuc	(0.016)	(0.011)	(0.008)	(0.005)	(0.009)	(0.010)	(0.006)	(0.004)	(0.008)	(0.013)
exper	0.023	0.012	0.007	0.007	0.024**	0.024*	0.013	0.005	0.035***	0.033*
enper	(0.016)	(0.012)	(0.008)	(0.007)	(0.008)	(0.010)	(0.009)	(0.004)	(0.008)	(0.013)
expersq	-0.023	0.027	-0.003	-0.006	-0.033	-0.026	-0.005	-0.003	-0.067***	-0.063*
enpersq	(0.034)	(0.033)	(0.014)	(0.012)	(0.018)	(0.022)	(0.018)	(0.007)	(0.013)	(0.023)
1.agecoh	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1.agecon	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2.agecoh	0.094	-0.026	-0.024	0.031	-0.008	-0.036	-0.008	0.049	-0.087	0.118
2.agecon	(0.094)	(0.074)	(0.024)	(0.031)	-0.008 (0.067)	-0.030 (0.064)	-0.008	(0.049)	-0.087 (0.056)	(0.090)
3.agecoh	0.091	-0.048	0.048)	0.085*	-0.078	-0.058	0.007	0.009	0.005	(0.090)
5.agecon	(0.091)	(0.048)	(0.042)	(0.083	(0.063)	-0.038 (0.062)	(0.053)	(0.009	(0.003)	
4 1	(0.094) 0.113	-0.023	0.022	(0.034) 0.078^*	-0.066	(0.062) -0.178 [*]	(0.053) -0.030	(0.030) 0.052	-0.003	0.047
4.agecoh										
- 1	(0.101)	(0.085)	(0.055)	(0.036)	(0.076)	(0.077)	(0.059)	(0.032)	(0.068)	(0.090)
5.agecoh	0.079	-0.195	0.015	0.045	-0.017	-0.167*	-0.067	0.028	-0.005	0.144
	(0.102)	(0.109)	(0.057)	(0.038)	(0.084)	(0.085)	(0.066)	(0.033)	(0.075)	(0.095)
female	-0.223**	-0.144*	-0.022	-0.084***	-0.117*	-0.133**	-0.080*	-0.048**	-0.117**	-0.107
	(0.070)	(0.064)	(0.029)	(0.019)	(0.045)	(0.050)	(0.032)	(0.015)	(0.036)	(0.056)
migrant	0.000	1.038***	-0.052	-0.061	0.000	0.021	0.411***	-0.006	0.083	-0.112
	(.)	(0.268)	(0.067)	(0.033)	(.)	(0.131)	(0.098)	(0.020)	(0.051)	(0.093)
2.jobtyp	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
3.jobtyp	-0.251*	0.035	-0.049	-0.045	-0.089	-0.051	-0.022	-0.177***	-0.017	-0.204*
	(0.105)	(0.135)	(0.039)	(0.029)	(0.067)	(0.100)	(0.071)	(0.027)	(0.073)	(0.087)
4.jobtyp	-0.218^{*}	-0.198	-0.160***	-0.172 ***	-0.260***	-0.078	-0.266**	-0.254***	-0.173**	-0.213*
	(0.111)	(0.151)	(0.044)	(0.032)	(0.068)	(0.108)	(0.087)	(0.030)	(0.066)	(0.099)
5.jobtyp	-0.248^{*}	-0.232	-0.235***	-0.151**	-0.366***	-0.202	-0.345***	-0.374***	-0.412***	-0.376*
	(0.118)	(0.142)	(0.052)	(0.050)	(0.090)	(0.125)	(0.078)	(0.047)	(0.069)	(0.121)
6.jobtyp	-0.319*	-0.401^{*}	-0.302***	-0.232***	-0.338***	-0.248	-0.201*	-0.297***	-0.353***	-0.356*

	(0.137)	(0.158)	(0.058)	(0.035)	(0.092)	(0.131)	(0.084)	(0.030)	(0.068)	(0.114)
7.jobtyp	-1.083***	-0.100	-0.404***			-0.082	-0.189	-0.452***	-0.714***	
	(0.237)	(0.371)	(0.087)			(0.162)	(0.097)	(0.103)	(0.208)	
8.jobtyp	-0.338*	-0.305	-0.254***	-0.194***	-0.334**	-0.381*	-0.278^{*}	-0.312***	-0.211	-0.390**
	(0.159)	(0.253)	(0.065)	(0.058)	(0.116)	(0.160)	(0.139)	(0.056)	(0.138)	(0.149)
9.jobtyp	-0.390*	-0.460^{*}	-0.282*	-0.375***	-0.351**	-0.344*	-0.289**	-0.406***	-0.249	-0.418**
	(0.153)	(0.203)	(0.129)	(0.072)	(0.123)	(0.144)	(0.104)	(0.079)	(0.209)	(0.136)
10.jobtyp	-0.172	-0.528**	-0.418***	-0.227***	-0.423***	-0.380**	-0.452***	-0.429 ****	-0.638***	-0.775***
	(0.275)	(0.192)	(0.068)	(0.058)	(0.094)	(0.129)	(0.092)	(0.051)	(0.103)	(0.168)
9.jobsec	0.000	-0.083	0.000	-0.529***	-0.179	0.403*	-0.068	-0.420**	-0.975***	-0.182
	(.)	(0.277)	(.)	(0.120)	(0.173)	(0.192)	(0.128)	(0.159)	(0.090)	(0.164)
11.jobsec	0.259	0.186	0.128		-0.354*	0.187	-0.165	0.069	-1.179***	0.071
10:1	(0.316)	(0.252)	(0.191)	0 < <	(0.144)	(0.134)	(0.103)	(0.165)	(0.208)	(0.143)
12.jobsec	-0.259	0.660**	-0.046	-0.667***	-0.208	0.028	-0.012	-0.221	-0.797***	0.085
12 1	(0.305)	(0.212)	(0.161)	(0.127)	(0.132)	(0.124)	(0.207)	(0.154)	(0.165)	(0.138)
13.jobsec	0.238	0.296		-0.813***	-0.364	0.231	-0.882***	-0.296*	-0.554**	-0.057
14 johana	(0.292) 0.890**	(0.272) 0.584**	0.210*	(0.203) -0.563***	(0.202)	(0.150) 0.161	(0.173) -0.108	(0.146)	(0.207)	(0.195) -0.131
14.jobsec	(0.310)	(0.384)	0.310 [*] (0.137)	(0.112)	-0.184 (0.149)	(0.084)	(0.108)	-0.247 (0.143)	-0.731*** (0.113)	(0.102)
15.jobsec	0.163	0.314	0.370***	-0.049	-0.261	-0.151	-0.389***	-0.453^{**}	-0.457***	-0.443*
15.j003ee	(0.305)	(0.193)	(0.096)	(0.129)	(0.195)	(0.141)	(0.102)	(0.146)	(0.125)	(0.182)
16.jobsec	-0.281	1.117***	0.204*	-0.497***	0.034	0.121	0.044	-0.157	-0.815***	-0.581
10.500.000	(0.311)	(0.200)	(0.098)	(0.150)	(0.221)	(0.263)	(0.106)	(0.161)	(0.092)	(0.548)
20.jobsec	0.148	0.201	0.004	-0.753***	-0.280	-0.147	-0.315***	-0.349*	-0.732***	-0.500***
5	(0.334)	(0.154)	(0.129)	(0.130)	(0.152)	(0.091)	(0.083)	(0.144)	(0.128)	(0.150)
21.jobsec	0.378	0.400^{*}	0.230**	-0.640***	-0.114	0.172^{*}	-0.140	-0.339*	-0.753***	-0.156
	(0.282)	(0.173)	(0.084)	(0.118)	(0.117)	(0.086)	(0.083)	(0.142)	(0.069)	(0.093)
22.jobsec	0.371	0.277	0.014	-0.784***	-0.361**	-0.102	-0.236*	-0.496***	-0.997***	-0.499***
	(0.289)	(0.194)	(0.090)	(0.118)	(0.123)	(0.087)	(0.093)	(0.142)	(0.072)	(0.100)
23.jobsec	0.356	0.157	0.160	-0.677***	-0.392**	-0.081	-0.173	-0.373**	-0.817***	-0.312^{*}
	(0.284)	(0.193)	(0.089)	(0.119)	(0.124)	(0.095)	(0.095)	(0.142)	(0.065)	(0.132)
24.jobsec	0.005	0.365	0.130	-0.564***	-0.386**	0.081	-0.080	-0.396**	-0.938***	-0.745***
05 1 1	(0.358)	(0.278)	(0.119)	(0.159)	(0.147)	(0.162)	(0.198)	(0.149)	(0.152)	(0.222)
25.jobsec	0.270	0.651	-0.319	-0.691***	-1.232***	0.304**		-0.158	-0.948***	0.141
7.jobsec	(0.343)	(0.340) 0.000	(0.196)	(0.140)	(0.102) 0.000	(0.100) 0.000	0.000	(0.186)	(0.110)	(0.129) 0.000
7.J00sec		(.)			(.)	(.)	(.)			(.)
10.jobsec		0.689***	0.389***	-0.636***	-0.082	-0.133	(.)	-0.221	-0.822***	0.092
10.j00500		(0.196)	(0.102)	(0.137)	(0.153)	(0.203)		(0.144)	(0.116)	(0.138)
17.jobsec		0.716***	0.372*	-0.551***	0.016	0.050		-0.505***	-1.014***	-0.157
		(0.206)	(0.150)	(0.130)	(0.283)	(0.162)		(0.143)	(0.094)	(0.158)
18.jobsec		0.976***	0.348***	()	-0.217	-0.209*		-0.297	-0.350***	0.066
5		(0.180)	(0.094)		(0.148)	(0.093)		(0.154)	(0.082)	(0.140)
19.jobsec		0.638**	0.307^{*}	-0.650***	-0.281	-0.040	-0.132	-0.346*	-0.592***	-0.076
		(0.221)	(0.137)	(0.130)	(0.181)	(0.115)	(0.112)	(0.156)	(0.137)	(0.145)
26.jobsec		-0.168					-1.293***			
		(0.224)					(0.135)			
8.jobsec				0.000	0.185			0.000	0.000	
				(.)	(0.163)			(.)	(.)	
27.jobsec									-0.592***	
0005	6 750***	8.524***	2.160***	5 500***	2 101***	0.410	1.984***	5 221***	(0.091)	2.002***
_cons	6.759 ^{***} (0.548)	8.524 (0.303)	2.160 (0.162)	5.589*** (0.170)	2.181*** (0.223)	0.419 (0.264)	(0.165)	5.221 ^{***} (0.161)	2.967*** (0.203)	2.002 (0.297)
N	264	312	434	637	370	495	444	794	770	360
R^2	0.428	0.601	0.545	0.501	0.581	0.498	0.518	0.511	0.520	0.476
	0.120	5.001	5.5 15	5.501	5.501	5.170	5.510	5.511	5.520	0.170

Least squares regressions weighted by sampling weights. Dependent variable: log hourly wage. Sample: full-time employees aged 35-54. Numeracy score standardized to std. dev. 1 within each country. Experiencesq divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; \mathbb{R}^2 refers to within-country \mathbb{R}^2 . Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Table A13. Model 8 Numeracy scores and firm-size

Table A13

	Pooled	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
11- 50	0.099***	0.251	0.286^{*}	0.064	0.125	0.172	0.083	-0.038	0.120	0.358*	0.152
	(0.019)	(0.132)	(0.118)	(0.068)	(0.158)	(0.090)	(0.073)	(0.098)	(0.085)	(0.141)	(0.113)
51 - 250	0.157***	0.251*	0.213	0.097	0.201	0.224^{*}	0.165*	0.175	0.129	0.359*	0.190
	(0.016)	(0.127)	(0.119)	(0.070)	(0.156)	(0.090)	(0.082)	(0.099)	(0.092)	(0.144)	(0.130)
250-1000	0.223***	0.525***	0.296^{*}	0.208^{**}	0.133	0.239^{*}	0.352***	0.152	0.133	0.476^{**}	0.172
	(0.027)	(0.132)	(0.128)	(0.074)	(0.221)	(0.106)	(0.098)	(0.123)	(0.099)	(0.158)	(0.121)
1000 +	0.308***	0.531**	0.594^{***}	0.246^{**}	-0.808	0.373***	0.250	0.281^{*}	0.282^{**}	0.613***	0.446^{**}
	(0.037)	(0.168)	(0.124)	(0.083)	(0.647)	(0.106)	(0.149)	(0.132)	(0.109)	(0.148)	(0.141)
_cons	-0.810***	-0.945***	-0.892***	-0.716***	-0.928***	-0.873***	-0.858***	-0.859***	-0.831***	-1.066***	-0.802***
	(0.015)	(0.109)	(0.100)	(0.056)	(0.122)	(0.078)	(0.057)	(0.073)	(0.069)	(0.126)	(0.084)
Ν	26925	789	887	5440	833	1904	1470	1158	1258	996	843
R^2	0.008	0.029	0.025	0.006	0.033	0.010	0.009	0.008	0.006	0.027	0.013

	Italy	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Spain	Sweden	U.K.	USA
11- 50	0.399***	-0.002	-0.020	0.244	0.052	0.174	0.071	0.038	0.052	-0.146	0.063
	(0.120)	(0.099)	(0.101)	(0.132)	(0.099)	(0.152)	(0.104)	(0.088)	(0.114)	(0.132)	(0.128)
51 - 250	0.282*	0.204*	0.153	0.222	0.172	0.285	-0.015	0.255**	0.147	0.062	0.107
	(0.121)	(0.101)	(0.093)	(0.127)	(0.099)	(0.157)	(0.106)	(0.088)	(0.113)	(0.120)	(0.120)
250-1000	0.272	0.384***	0.151	0.293*	0.318**	0.333	-0.013	0.225	0.347**	-0.054	0.241
	(0.249)	(0.113)	(0.121)	(0.139)	(0.108)	(0.178)	(0.145)	(0.126)	(0.127)	(0.154)	(0.127)
1000 +	0.207	0.606***	0.457***	0.297*	0.307**	0.465*	-0.031	0.051	0.380**	0.017	0.391**
	(0.147)	(0.106)	(0.108)	(0.150)	(0.105)	(0.200)	(0.178)	(0.147)	(0.126)	(0.130)	(0.123)
_cons	-0.937***	-0.862***	-0.825***	-0.917***	-0.847***	-1.043***	-0.790***	-0.650***	-0.945***	-0.508***	-0.756***
_	(0.087)	(0.074)	(0.062)	(0.110)	(0.081)	(0.120)	(0.083)	(0.065)	(0.093)	(0.103)	(0.104)
Ν	773	1089	915	868	1222	556	1008	964	1086	1445	968
R^2	0.019	0.036	0.020	0.007	0.014	0.014	0.001	0.012	0.016	0.006	0.017

Least squares regressions weighted by sampling weights. Dependent variable: log numeracy scores. Sample: full-time employees aged 35-54. Numeracy score standardized to std. dev. 1 within each country. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2 . Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001