Does Cognitive Skill Explain Rising Wage Inequality in OECD Countries?*

Kentaro Asai†

Under the supervision of Thomas Breda

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Abstract

Using micro data from the two OECD skill surveys, this paper examines the role of cognitive skills in explaining the rise of wage inequalities. I find that basic cognitive skills have increased wage inequality in the majority of 6 countries studied. Most of its contribution come from the change in return to cognitive skills, rather than from the distribution of the skills. An additional evidence suggests that the role of education previously thought responsible for wage inequality partially reflected the effect of cognitive skills. The finding here is consistent with the view that the recent technological change has increased the demand for cognitive skills.

Keywords: Labor economics, inequality, cognitive skill
JEL Classification: J24, J31

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†Paris School of Economics. Email: kentaro.asai76@gmail.com

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1 Introduction

The last couple of decades have seen a great transition in the nature of economy across the globe. With the rise of inequality in a variety of economic measures, national-level economic performance and individual's welfare have been decoupled. The world economy is stratified more horizontally than vertically, as compared to before.

Wage inequality is one important measure of inequality, as wage summerizes fundamental features of how workers are rewarded in the labor market. The rise of male wage inequality is observed in many advanced countries, particularly in the Untied States. Economists' account for the rising male wage inequality in the US since the 1970-80s have mainly four branches: institution, including minimum wage (DiNardo, Fortin, & Lemieux, 1996; Lee, 1999; Autor, Manning, & Smith, 2016) and unionization (Card, 1996, 2001); labor market compositions, such as increase in low-skilled immigrants, female labor force participation and college graduates (Katz, 1994; Topel, 1997); relative labor demand and supply, including skill-biased technological change (Acemoglu, 1998; Goldin & Katz, 2008); globalization (Krugman, 2008; Miller, 2001). Although the literature is far from fully accounting for the great transition of inequalities, there is a general consensus that the shift in skill demand due to the technological change played an important role (Acemoglu, 2002; Autor, Katz, & Kearney, 2008). Autor, Levy, and Murnane (2003) documents an increase in jobs content with non-routine (non-manual) cognitive tasks. As a consequence, labor market has been polarized, with higher share of high-paying jobs and low-paying jobs in the US and in Europe (Autor, Katz, & Kearney, 2006; Goos, Manning, & Salomons, 2009).

Skilled-biased technological change has induced a sharp rise of return to schooling, stretching wages across education distribution. At the same time, it is also well documented that wage inequalty has risen within narrowly defined skilled group; put simply, the rise of wage inequality is also obseved within workers of same educational level (Juhn, Murphy, & Pierce, 1993; Lemieux, 2006a). This implies a role of skills that are not observable. In this light, several bodies of research attempt to account for such within-group inequalities: role of unmeasured skills, including cognitive skills (e.g. Murnane, Willett, and Levy (1995); Autor et al. (2003)), social behaviour (e.g. Heckman, Stixrud, and Urzua (2006)) and subjects of study (e.g. Lindley and McIntosh (2015)). Among them, research on the impact of cognitive skills on wage inequality have grown substantially during the recent decades, owing in part to a series of international surveys conducted by the OECD, which provide a numerical measure of cognitive skills of adult population. These surveys are: the International Adult Literacy Survey (IALS), administered between 1994 and 1998; the Adult Literacy and Life Skills Survey (ALL), administered between 2003 and 2007; the Survey of Adult Skills or Programme for the International Assessment of Adult Competencies (PIAAC), administered in 2012[1]. These surveys conduct cognitive tests, such as of literacy and numeracy, and provide standardized scores in 500 scale, that are comparable across countries and time[2]. In contrast to PISA or other test scores and grades in school often used in the literature, they provide

[1]Detailed description of these data will be provided in the next section

[2]Comparability between surveys are discussed in detail later.

the measure of cognitive skills of adult population (aged 18 to 65). Since the micro data of these surveys contain respondents' labor market information, these surveys allow to assess how wage inequality is determined by the distribution of cognitive skills in the labor force and by the price of such skills.

In fact, some papers has used these datasets to study the relationship between cognitive skills and wage inequality. For example, Devroye and Freeman (2001) and Blau and Kahn (2005) apply a variance decomposition technique to IALS and find only a small power of cognitive skill in explaining international differences in wage inequality. A similar conclusion is made by Paccagnella (2015) that implements a different decomposition method using PIAAC datasets. It also indicates that difference in schooling plays much bigger role than cognitive skills in explaining the cross-country inequality differences. On the other hand, Leuven, Oosterbeek, and van Ophem (2004) and Broecke, Quintini, and Vandeweyer (2018) introduce a relative supply and demand framework developed by Katz and Murphy (1992), and show that the dispersion of cognitive skills does explain a fair portion of variation in cross-country wage inequality observed in IALS and in PIAAC respectively. From these studies, overall, it seems that cognitive skills have relatively small or modest explanatory power for international differences in wage inequality. Education is generally found to play a larger role.

In this paper, I investigate if cognitive skills can explain the rise of wage inequalities over time. This is an important extension from the previous literature that focus on the variation across countries, because, as mentioned, a considerable attention is paid to the rise of wage inequality in the last several decades observed in many developed countries. Some evidence suggest that the increase in wage inequality is due in part to the rising demand for cognitive abilities precipitated by the rapid technological advancement (Autor et al., 2006; Goos et al., 2009). Yet, little empirical investigation has been done, using an actual measure of cognitive skills. Instead, most of the previous study, such as Autor, Katz, and Kearney (2005), uses years education, due to the lack of quantitative measure of cognitive skills possessed by labor force. Education, however, cannot separate different types in a skill set, including cognitive skills, networking and social behavior. Equally importantly, educational attainment is not necessarily comparable across time and generations, because of a number of education reforms conducted[3] and birth cohort differences[4]. In fact, a work by Carneiro and Lee (2011b) suggests that the average quality of college graduates has declined from 1960 to 2012, as a consequence of more people obtaining a university degree. Gratefully, IALS and PIAAC provide numerical measures of cognitive skills that are comparable across time periods. This allows to directly investigate whether and how much cognitive skills have contributed to the wage inequality over time.

With regards to the methodology, this paper uses a detailed variance decomposition method proposed by Machado and Mata (2005) that has been applied in many studies since

[3]There are simply too many examples of educational reforms, but see, for example, the change in compulsory education and recent higher education reforms in Europe (Brunello, Fort, & Weber, 2009; Murtin & Viarengo, 2011), compulsory education reform in Canada (Oreopoulos, 2006), and curriculum reform in Japan (Tsuneyoshi, 2004).

[4]See, for example, Barrett and Riddell (2016).

its publication. This enables to decompose the difference in wage distributions into the contribution of each variable. One drawback common in most of the listed previous works was that they could only examine the price effect and composition effect of all explanatory variables combined[5]. However, since this paper aims at identifying the extent to which cognitive skills alone have increased wage inequality over time, it is crucial to distinguish the effect of subcomponents. It is thanks to this method that the marginal effect of cognitive skills, the main interest of this paper, can be estimated. In brief, the methodology builds upon conditional quantile regression. Through simulations involving estimated quantile coefficients, this methodology allows a full characterization of counterfactual wage densities. Based on these densities, one can decompose the change in wage inequality over time into each variable's contribution through price effect (i.e. the effect due to the change in coefficients) and composition effect (i.e. the effect due to the change in distribution of the covariate).

I argue that cognitive skills have made a sizeable contribution to the rise of wage inequality between 1994 and 2012 in the 4 of 6 countries studied (Denmark, Finland, Norway and Slovenia), contrary to the majority of previous findings of cognitive skills' small role. Its contribution comes mostly from the change in return to cognitive skills, rather than from its distribution. Such price effect of cognitive skills is shown as strong as that of education. This is consistent with the view that the technological advancement has increased the premium of cognitive skills and it resulted in the rise of wage inequality. At the same time, it also indicates that education still captures a part of human capital that contributed the wage inequality, be one's behavior, networks or other skills not measured by basic cognitive skills. Nonetheless, such role of education seems to be over-emphasized in the previous literature, as the explanatory power of education drops once cognitive skills is added to the decomposition. It is also found that, despite the addition of cognitive skills in the model, residuals still remain substantial. Finally, it is important to stress that there is a variation across countries in terms of the result. Notably, in Czech Republic and Italy, cognitive skills have rather decreased wage inequality over the span of 20 years.

This paper is relevant in a number of topics in economic literature, including studies on inequality and on demand and supply of skills in the labor market. In addition, it gives some insights to policy discussions, especially in the field of education. There are some movements in school to focus on developing skills of students necessary for labor market. Indeed, European Commission now emphasizes the development of children's literacy and numeracy skills[6]. Taken the empirical findings here at face value, such policies to increase the cognitive skills of children might not lead to an increase in inequality as the composition effect turns out to be negligible. Rather, if supply of workers with high cognitive skills increases, then it is possible that the return to cognitive skills decline, pushing inequality downward.

The structure of this paper is as follows. In the next chapter, I explain the data used for this paper, provide descriptive statistics and a some theoretical framework in studying cognititive skills. In chapter 3, I examine a cross-country level relationship between wage inequality and return to cognitive skill, as well as a relationship between wage inequality and cognitive

[5] Yet, Blau and Kahn (2005) attempts to infer the marginal contribution by running two different models with and without cognitive skills.

[6] See: http://ec.europa.eu/education/policy/school_en

skilll inequality. In chapter 4, being the main content of this paper, I perform a detailed decomposition analysis to examine the role of cognitive skills in explaining the change in wage inequality over time. The last chapter concludes.

2 Data, Descriptive Statistics and Theory

2.1 Data

OECD skill surveys

The OECD has conducted three international surverys on adult cognitive skills since the 1990s, so as to provide internationally comparable measures of adult skills relevant in the labor market. Those three surveys are: the International Adult Literacy Survey (IALS), administed between 1994 and 1998; the Adult Literacy and Life Skills Survey (ALL), administered between 2003 and 2007; the Survey of Adult Skills or Programme for the International Assessment of Adult Competencies (PIAAC), administed in 2012 and in 2014. Hereafter, each survey is simply referred to as IALS, ALL and PIAAC respectively. All these surveys, in the form of tests, quantify cognitive skills (e.g. literacy and numeracy) of adult population, aged 16- to 65-years old, in the 500 scale[7]. 23 countries and regions participated in IALS, 11 countries participated in ALL, and 33 countries participated in PIAAC (24 in the first round, and 9 in the second round). The skills measured in these surveys are general or basic skills that are used in labor market as well as in daily occasions, rather than specific or professional skills[8]. In this paper, only IALS and PIAAC will be used, since the number of participating countries is much less in ALL and hence the comparison of the surveys becomes difficult once all three surveys are used. Detailed information of IALS and PIAAC is provided below.

IALS and PIAAC

IALS is the first OECD survey on adult skills and it was administered between 1994 and 1998. 23 countries and regions participated in the survey. Its main objective is to provide an internationally comparable measure of literacy skills[9], so as to help understand the level and the distribution of literacy skills that were deemed gaining more imporatnce in the labor market. Literacy skills assessed in the survey are cognitive skills in three separate domains: prose literacy, document literacy and quantitative literacy[10]. All of these skills are measured in a 0-500 scale based on a paper-based assessment. Along with it, it also provides information on respondents' social and economic characteristics. The target population ranges from ages 16 to 65, and the survey implements careful sampling and weighting procedures to make

[7]Perhaps, the most intuitive way to think of these surveys is the ”adult version of PISA”.

[8]Discussion on the relevance of measured cognitive skills in the labor market, and its distinction from other skill measures such as education, will be discussed later.

[9]Literacy is defined as ”the ability to use printed and written information to function in society, to achieve one's goals, and to develop one's knowledge and potential”.

[10]Prose literacy refers to ”the ability to read and use texts of varying levels of difficulty that are presented in sentence and paragraph form, including editorials, news stories, poems, and fiction”; document literacy is ”the knowledge and skills required to locate and use information contained in formats such as job applications, payroll forms, transportation schedules, maps, tables, and graphics”; quantitative literacy is defined as ”the knowledge and skills required to apply arithmetic operations, either alone or sequentially, to numbers embedded in printed materials, such as balancing a checkbook, calculating a tip, completing an order form, or determining the amount of interest on a loan from an advertisement”.

sure the representativity of samples from each participating country, in order to facilitate international comparisons. Sample size ranges from 1500 to 8000.

PIAAC is the third survey on adult cognitive skills that OECD has administered in 2012 and in 2016, involving 33 countries in total. It measures literacy (a combination of prose and document literacy), numeracy and problem solving in technology-rich environment[11]. Although the main features of the survey are similar to those of IALS, PIAAC extends its scope of skills to those relevant in the age of information technology. It also adopts a computer-based assessment[12]. General sampling and weighting schemes are the same as IALS, but PIAAC in general has more samples, having at least 5000 respondents for each country, with the largest of 27000.

The basic information of these two surveys are summarized in Table 1.

Comparability of the data

This paper uses both IALS and PIAAC to explore the possible effect of cognitive skills on the wage inequality evolution. Despite that these two are not identical and conducted over a gap of 20 years, similarities in measured skills and in data collection procedures make sure the comparability of the two.

With respect to the measured skills, PIAAC considers literacy skills more broadly than IALS does. IALS measures separately the prose and document literacy, whereas PIAAC measures them in a single category of ”literacy”. Gratefully, the OECD provides a single literacy score of IALS by rescaling prose and document literacy, to be able to compare it to the PIAAC literacy. Moreover, in spite of the difference in the form of tests (computer-based or paper-based), conceptualization of cognitive abilities required in the test is essentially similar, so are factors affecting the level of question items (OECD, 2016). Furthermore, there is a substantial overlap (around 60%) of question items between the two. For these reasons, literacy skills between IALS and PIAAC can be seen quite comparable.

On the other hand, numeracy measured in PIAAC is not comparable to quantitative literacy in IALS. Numeracy is much broader than quantitative literacy which involves mainly arithmetic operations based numerical information written in text. In contrast, numeracy also includes solving questions with more various situations and mathematical information. The OECD, therefore, does not consider these two measures share the same concept. Yet, regarding terminology, both will be simply referred to as ”numeracy” in what follows, in order to make a clear distinction between ”literacy” skills discussed above which does not entail mathematical

[11]Literacy in PIAAC is defined as ”understanding, evaluating, using and engaging with written texts to participate in society, to achieve one’s goals, and to develop one’s knowledge and potential”; Numeracy refers to as ”the 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”; problem solving in technology-rich environment is defined as ”the ability to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks. The first PIAAC problem-solving survey focuses on the abilities to solve problems for personal, work and civic purposes by setting up appropriate goals and plans, and accessing and making use of information through computers and computer networks.”

[12]However, paper-based tests were used for those not familiar to computers, so as to avoid selection bias due to the form of test taking.

knowledges and operations.

For the issue of comparability, this paper mainly uses literacy rather than numeracy in studying the effect of cognitive skills on wage inequalities. However, in reality, the correlation between literacy scores and numeracy scores is very high in both surveys, generally exceeding 90%. Thus, the similar conclusion is expected to be drawn even when non-comparable numeracy was used. To be prudent, however, results using numeracy scores is presented in the appendix. s

According to the OECD's documentation, sampling scheme, survey operations and response rates in the two surveys are also similar or do not affect the general comparability of the data. For more detailed discussion on these logistics, readers might refer to OECD (2016).

Samples used in this paper

Samples of respondents used in this paper is restricted to male who is working at the timing of survey. Blau and Kahn (2005) restricts to full-time employment with certain level of hourly wage. However, as the recent increase of inequality is partially affected by the shift of full-time employment to part-time one (OECD, 2011), non-fulltime workers are also included in the study. Note that all the following numbers and results presented in what follows come from these subsamples.

2.2 Descriptive Statistics

Cognitive skills

Here provides an overview of cognitive skills (of subsamples specified before) measured in IALS and PIAAC.

Table 2 and Table 3 summarize the distributional statistics of literacy and numeracy, respectively, of countries for which the data was available to the author. The upper section is of IALS in 1994 and the lower section is of PIAAC in 2012[13]. The columns 2-4 show respectively (sub)sample size, mean literacy score and coefficient of variation (i.e. standard deviation divided by mean). Next three columns are distributional statistics, showing 10th, 50th and 90th percentile values. The last three columns show ratios of these percentiles as inequality measures, although it will be metioned in greater detail in the tables presented later instead of here. The lowest row of each subsection of the tables shows a non-weighted average of each distributional statistics of all participating countries. With regards to IALS, the average literacy score of participating countries is 275.3 with the coefficient of variation around 0.16 (i.e. one standard deviation is around 44). Generally, each country's mean literacy seems concentrated around this international average, where sweden marking the highest country-average of 308.2 and Chile showing the lowest, 230.7. Percentiles, however, reveal a variation across countries in terms of score distribution. For example, despite that the average literacy is relatively similar, 10th percentile is considerably lower in the US than in Germany.

[13]The year of PIAAC is simply referred 2012 hereafter, although some countries' data were administered in 2014.

Yet, in general, countries with higher mean literacy exhibit higher scores at each percentile. With respect to PIAAC, the international average literacy is 268.2, slightly lower than that of IALS. The highest mean literacy is achived by Japan with 298.7, whereas the lowest is Chile's 223.1. The similar feature as before can be marked on the distributional varieties across countries from percentile values (e.g. Italy and Singapore).

Table 3 presents the same table for numeracy. It can be immediately seen that observed tendencies are very similar to those of literacy scores.

Figure 1 visualizes an entire distribution of IALS literacy and of PIAAC literacy for countries that paraticipated in both surveys. Figure 2 does the same for numeracy scores. In general, literacy scores seem slightly more stretched toward lower-tail and more dispersed in PIAAC in 2012, relative to IALS in 1994. This is in line with Barrett and Riddell (2016) that finds lower score levels of younger birth cohorts. This can be directly shown in previous tables, where the comparison between IALS to that of PIAAC relveals that there are more countries that experienced lowering of mean literacy. On the other hand, coefficient of variation does not necessarily increase in many countries.

Table 4 and Table 5 show inequality measures based on percentiles, for literacy and numeracy respectively. For each percentile ratio measure, level values of 1994 and of 2012 as well as its change over time are summarized. It seems first that in general the lower-tail inequality (P50/P10) is larger in magnitude than in upper-tail inequality (P90/P50). Furethermore, inequality level is generally higher in Angro-Saxon countries than in Nordic countries, suggesting a possible influence of cognitive skills on wage inequality. In many countries, inequality has risen over time. For example, Denmark experienced an increase of 0.22 in P90/P10 in 20 years. Interestingly, however, Angro-Saxon countries experienced little or even negative change in inequality measures.

Wage

Wage data used in this paper is hourly wages, imputed using earnings from work and hours worked. Due to the difference in the way question is asked in IALS and PIAAC, wage data are not perfectly comparable; notably in IALS one cannot be sure whether earnings information answered in the survey is before or after taxation, while PIAAC explicitly asks earnings before being subject to taxation and to other deductions. However, this is unlikely to cause a major problem for a number of reasons. First, since the paper uses (log of) hourly wages in most of the analyses, the influence of taxation and other deductions is minute. Furthermore, inequality values calculated using the wage data in IALS actually are similar to other sources, such as the OECD's and equally importantly there is no particular pattern of under/overstating of wage inequality observed when compared to the other data (shown later in tables). Lastly, indeed, when the author modifies the wage definition (e.g. imputing after tax income for 2012), the results barely changed. For these reasons, it is unlikely to cause a mojor problem to use wage data of IALS and PIAAC together.

A bigger problem for the analysis, however, is the limited availability of continuous earnings data in public-use micro dataset of IALS. In contrast to PIAAC which provides full wage information of almost all the countries in public files., there are only 9 countries (i.e.

Chile, Czech, Denmark, Finland, Hungary, Italy, Norway, Slovenia and Switzerland (Italian speaking)) for which continuous earnings data is made available in the public data of IALS. The rest of the countries's wages are reported only in the bracket sof 5 quantiles. Some papers succeed in obtaining continuous wage data of these countries by contacting directly to each country's study director of IALS, but it was no longer possible after 20 years have passed since the administration of the survey. Another attempt was made to ask Statistics Canada, who took care of IALS administration, but unfortunately the author was not granted a permission to use continuous wage data of the other countries by the time when this paper was written. For this reason, the main analyses will be carried out using rather small number of countries. The extension of this paper uisng more countries, including, for example, the Untied States, is therefore a future task.

Wage data are trimmed at the top and bottom of the wage distribution, so as to minimize the influence of outliers. Again, these wages are of male workers, including part-time and full-time.

Table 6 provides the wage inequalities in 1994. There are four measurs of inequality: coefficient of variation and three percentile ratios, namely P90/P10, P90/P50 and P50/P10. Calculated percentile ratios are compared to those of two other sources, since sample size of IALS is relatively small (between 500 and 2100) and, as said earlier, the wage definition of IALS is not perfectly clear. Different sources to be compared inculde Leuven et al. (2004) that use IALS but had an access to the detailed wage data of more countries, and OECD Employment Outlook 1996 which compiles earnings inequality information using each country's administrative data. For percentile ratios, values look relatively similar among the three. The US, Canada, Chile and Hungary exhibit higher inequalities in every measure, making a contrast with Denmark, Finland and Norway of lower inequalities .

Table 7 provides the same inequality indices from PIAAC data in 2012, with the reference to two other sources, including Broecke et al. (2018) that uses the same data and the OECD's Income inequality indicator which calculates inequality measures based on general income (i.e. not only income from labor). It is reassuring that the OECD calcualtes wage inequality using PIAAC in Employment Outlook 2015, reflecting that its wage data is well-defined and has a relatively large sample. As before, values are similar across the data sources, except that the OECD's tend to be learger than the rest, owing perhaps to its use of inequalities of broader income, which include non-labor income as well. The US's high income inequality is opulent, so is the lower inequality of Nordic countries. There seems more countries that have higher P50/P10 than P90/P50, although the magnitude does not stand out.

Table 8 shows the change from 1994 to 2012 in inequality measures for countries that participated in both surveys and whose wage data is available. The US is shown as a reference, althoguh its wage data is not available. The column "PIAAC" shows the changes calculated using available PIAAC and IALS data. The column "LOV" uses the same for 2012, however using the values from Leuven et al. (2004) for 1994. The "OECD" column presents values computeed using the OECD data for both 1994 and 2012 that are shown in the previous two tables. At first glance, the similarity among the three is not as strong as it is in inequality levels (of the previous tables). Sometimes signs are not the same, so are magnitudes, questioning the validity of the inequality changes calculated using IALS and PIAAC. However, there is a reason to believe that the calculated ones are not far from the reality. Remembering that the OECD's 2012 inequality values are inflated due to the use of income rather than wage, wage inequalities should actually be lower than these values. On the other hand, the values of LOV are suspected to be too low. For example, between 2004 and 2012, income inequalities have slightly risen in Norway, according to OECD Income inequality indicator, as opposed to the negative sign seen in LOV[14]. Similarly, the negative sign on the US seems counterintuitive, since the rise of wage dispersion is well-accepted in the literature. Thus, LOV values seem somewhat too low for them to mirror the reality. Fortunately, values in the PIAAC column generally fall in between these two alternatives. Therefore, the values computed using available IALS and PIAAC wage data better capture the reality of wage inequalities.

According to this table, most of the countries have experienced a rise in percentile ratios, except Slovenia. Chile seems to have experienced the shapest rise, contrasted to the modest change of Nordic countries. It is counterintuitive that the coefficient of variation has dropped in many countries. Thus, coefficient of variation may not serve as a good indicator of inequalities that have risen over time, and hence the focus of the paper will be mainly on percentile ratios[15].

2.3 Why cognitive skills matter

This subsection explains the relevance of cognitive skills measured in IALS and PIAAC in the labor market.

Cognitive skills in economic theory

As mentioned in the introduction, inequality in the labor market is determined in part by labor demand and supply. By studying the effect of cognitive skills on inequalities, this paper is primarily concerned with the labor suppley side, i.e. the distribution of workers' characteristics. Gary Becker's famous human capital model proclaims that people invest in human capital, through education, job trainings and health maintenance, and it in turn increases wages. Human capital is a rather vague concept and it is a miscellaneous of various factors affecting one's labor market outcomes, including knowledge, skills, personality and health. We would expect that cognitive skills constitute a part of human capital, since they help a worker process information, analyze, derive solutions and so on[16].

A unique advantage of IALS and PIAAC in this regard is that they provide direct measures of such cognitive skills. This is an important progress from the tradition of proxying human capital simply by years of education, which fails to disentangle different elements of human capital. It is critical that the recent rise of inequality is observed not only between educational groups but also within a group, which points to the existance of a component in skills whose distribution and/or return have seen a considerable transition. This motivates an examination

[14]2004 is the earliest year for which inequality mesure is available in the OECD Inequality indicator.

[15]It is possible to use Gini coefficient instead of coefficient of variation. However, it turned out that Gini coefficient based on wage data tended to be too small compared to the one calculated using income data, and does not provide much a meaninngful implications. For this reason, Gini coefficient is not used in this paper.

[16]Hanushek and Woessmann (2008) separates human capital into cognitive skills, non-cognitive skills and error term: $H = C + N + \mu$.

on whether such component is cognitive skill or not[17]. There is indeed some evidence suggesting the importance of cognitive skills. Acccording to Hanushek, Schwerdt, Wiederhold, and Woessmann (2015), return to cognitive skills (measured in PIAAC) rises as a worker accumulates more experience, possibly because employers can detect workers' true ability (i.e. cognitive skills) as her work history accumulates, in contrast to the return to education that serves a larger role as a signal at the early stage of her career[18]. Furthermore, a recent macro-level evidence from Hanushek and Woessmann (2012) shows a strong relationship between cognitive skills (measured in PISA) and economic growth rate between 1960 and 2000 and even finds much larager explanatory power of cognitive skills than education. In additiona, from the perspective of demand side, there is evidence suggesting a shift in job content that favors non-routine cogntive tasks compared to the past(?, ?). Given these findings combined, cognitive skills rather than education could capture the evolution of wage inequalities. It is important to note that, even after cognitive skills is controlled for, education may still capture the other parts of human capital, such as personal traits, network and other skill sets.

In practice, education and cognitive skills are strongly connected. Education can raise one's cognitive ability, on one hand, and one with higher cognitive skills may continue her study longer, on the other hand. Figure 3 visualizes such relationship at cross-country level. The top two graphs plot IALS literacy and numeracy score respectively against average years of education in 1994, by country. The bottom two do the same for 2012 and PIAAC. Clearly, measured literacy and numeracy are strongly correlated to level of education. A recent work by Carlsson, Dahl, Öckert, and Rooth (2015) identifies a causal impact of education on cognitive skills, thus there is a fair chance that this correlation partially reflects the causality.

Cognitive skills and labor market outcomes

Figure 4 demonstrates that at macro level measured cognitive skills are associated with labor market outcomes. The top two graphs plot GDP per capita in 1994 agaisnt mean IALS literacy and numeracys by country. The bottom two graphs do the same for 2012, against PIAAC scores. A sharp upward line implies that cognitive skills and capacity to produce are strongly related. For example, for literacy, an increase in mean literacy score by 10 is associated with an increase in GDP per capita by 5185 dollars and by 5130 dollars respectively in 1994 and in 2012. Such magnitude can considered very high. Of course, this is not entirely causal, but it is in line with the findings from the previous literature that cognitive skills matter in economic development and labor market performances (Cawley, Heckman, & Vytlacil, 2001; Hanushek & Woessmann, 2008, 2012).

To see explicitly the effect of cognitive skills on labor market outcomes, return to literacy and numeracy on wages at micro-level is useful. Figure 5 summarizes return to cognitive skill scores. Top two graphs are of 1994 based on available IALS data (respectively, literacy

[17] Although this paper cannot study the case of the US, based on which many papers are publsihed, due to the limited availability of the data, it is still interesting to investigate it for other countries.

[18] Asai, Breda, Rain, Romanello, and Sangnier (2018) does not find such increasing return to cognitive skills along work experience, but the return is flat over a career. Yet, this also means that cognitive skills is stably important.

and numeracy), and the bottom two are of 2012 based on available PIAAC data. Each bar represents return to literacy/numeracy score in each country, calculated based on regressions using each country's subsamples. Darker bars are based on the modified Mincer regression in which log of hourly wage is regressed on literacy/numeracy (instead of years of education) and polynomial of years of experience, that is:

$$W_i = \alpha + \beta_1 C_i + \beta_2 E_i + \beta_3 E_i^2 + \epsilon_i \quad \text{(Modified Mincer model)}$$

where W_i is log of hourly wages, C_i represents cognitive skills (i.e. literacy/numeracy scores), E_i and E_i^2 are years of experience and its quadratic form, and ϵ_i is the error term. On the other hand, light-colored bars are based on the regressions that *add* (not replace literacy with) years of education in this specification, so that:

$$W_i = \alpha + \beta_1 C_i + \beta_2 E_i + \beta_3 E_i^2 + \beta_4 S_i + \epsilon_i \quad \text{(Complete model)}$$

with S_i being years of schooling. To faciltate international comparisons, marginal effect (i.e. regression coefficientof literacy/numeracy, β_1) is standardized by way of multiplying by each country's standard deviation of literacy/numeracy scores. As a consequence, each bar times 100 would answer the following question: "By how much percent does hourly wage increase if a worker's literacy score increase/numeracy by one standard deviation in each country?".

We can see first, from the modified Mincer regression, that cognitive test scores are associated with wages. One standard deviation increase in cognitive test scores is associated with the wage rise of around 10% to 20% in 1994 (except Chile), regardless of literacy or numeracy. There is, however, a considerable variation in the magnitudes among countries (e.g. Denmark's 9% versus Chile's 46%), implying that the return to skills are affected by different market conditions. Secondly, we can see that the return drops in all countries once eduation is added in the regression, although the amount of such change greatly varies. In some countries such as Denmark and Czech Republic, the return gets more than halved, whereas in other countries like Finland, the decline is modest. Such decline of the return stems from the high correlation between literacy/numeracy and education, as discussed earlier. For example, those with higher literacy/numeracy tend to go to the school longer, and schooling, not through increasing in cognitive abilities, affects wages. A similar point has been raised in Asai et al. (2018) that, using PIAAC data too, states "explanatory power of numeracy skills is substantially embedded in the one of schooling years" (p.68). From the bottom two graphs of 2012, a similar conclusions can be drawn. An interesting finding using PIAAC, however, is that Nordic countries that have lower inequality exhibit lower returns, whereas countries with higher inequality, such as Japan and Great Britain, have higher returns, as far as the modified Mincer equation is concerned. Hanushek et al. (2015) extends this point and finds that the variation in returns are partially related to unionization, employment protection, and size of public sector. However, as seen in the table, once education is included in the regression, such pattern becomes less articulated.

From these descriptive data, the fact can be reasonably established that measured cognitive skills are associated with wages, although the magnitude can be variant across countries. Given that cognitive skills assessed in IALS and PIAAC are relevant in the labor market, it would be interesting to investigate a possible impact of cognitive skills on the rising wage inequalities in recent decades.

3 Cognitive skills and wage inequality at cross-country level

This chapter explores the relationship between cognitive skill measures and wage inequality, by looking at a number of descriptive statistics at macro level. From this chapter, all the results shown are of literacy, and all the results using numeracy are provided in appendix.

There are two possible channels through which cognitive skills determine the level of wage inequality. One is price effect: higher return to cognitive skills lead to more dispersion of wages and increase inequality. The other is composition effect: the more dispersed cognitive skill distribution is, the more dispersed wage becomes, keeping the return constant.

3.1 Price: return to cognitive skills and wage inequality

If price effect actually exists, then, at macro level, we would expect that a country with higher return to literacy/numeracy have higher wage inequalities. Hanushek et al. (2015), using PIAAC data, in fact suggests that a variation in return to cognitive skills across countries is related to a number of market structural and institutional factors, such as level of employment protection, which also influence wage inequality.

Table **??** compares coefficients in 1994 and in 2012, using literacy as a measure of cognitive skills. There are three specifications: Complete model where log of hourly wages is regressed on log of literacy, years of education and experience (and its squared); the modified Mincer equation where only log of literacy and experience (and its squared) are included; (usual) Mincer equation, putting education and experience (and its squared) as regressors. Standard errors are not reported to save space, but significance level is shown. Coefficients of squared experience is also omitted from the table. The coefficients of literacy in the table slightly different from those presented in Figure 5, because it is taken log (so that each coefficient represents elasticity) and it is not multiplied by standard errors to avoid being affected by composition effect, which will be studied separately. With regards to the return to (log of) literacy, looking at the modified Mincer model, there seems more countries that saw an increase in return than those did not. For example, Norway has the most notable change, where the elasticity has changed from 0.494 to 0.693. Similarly, in Complete model where education is controlled for, return has increased from 1994 to 2012 in most of the countries with the exception of Chile and Finland. These are consistent with the view that return to cognitive skills have increased over time, due partially to technological changes[19].

On the other hand, both in Complete model and in usual Mincer model, the return to education has increased in virtually all the countries during the period 1994-2012. This is consistent with a number of findings that return to education has been increasing (**cite a paper**). Return to experience tends to be lower in 2012, although it is not as systematic as the return to education. The fact that the change in return to education is positive even after controlling for literacy implies the growing importance of education, although through what channels (e.g. non-cognitive skills) education impacted on wages remain inconclusive.

[19] It also reflects the economic growth. However, note that even in countries like Italy that did not experience much economic growth, return to cognitive skills have increased.

A similar conclusions can be made from the numeracy version, shown in the appendix.

Now, it is directly investigated the relationship between the wage inequality and return to cognitive skills. Figure 6 visualizes a cross-sectional relationship between the return to literacy and the wage inequality in 1994 based on available IALS data. Left column uses the return to literacy from the modified Mincer model (i.e. without education control) and the right column uses that from the Complete model (i.e. with education control). Each row shows different inequality measures, namely log of percentile ratio of P90/P10, P90/P50 and P50/P10, plotted against the return to literacy. Chile and Hungary are removed from the figures, since these were outliers. Looking at the left three boxes, only a slight positive correlation can be found between wage inequalities and return to education in the modified Mincer model. However, turning to the right three boxes, the relationship is strong for P90/P10 and P90/P50 when the return to literacy controlled for education is used (with very high R^2). It is almost null in 50/P10, on the other hand.

Figure 7 does the same exercise, using PIAAC data of 2012. Since the number of countries for which wage data was available is larger, the relationship can be seen more clearly than the previous table. It seems that there is a modest but positive relationship between inequality measures and return to literacy in 2012 too. It is again stronger for the one that uses return to literacy controlled for education. It seems in both periods of 1994 and 2012, there is a positive association of return to literacy skills and the level of wage inequality at macro-level.

However, with a country-level cross-sectional data, there are a lot of factors ignored and causality is hardly identified. It might be a spurious correlation due to the difference in intitutional factors. For this reason, Figure 8 plots *change* in wage inequalities against *change* in return to literacy. This can be though of as a kind of difference in difference approach. Of course it is still far from the causality, but at least some time-robust institutional factors become less influential. Unfortunately, given the number of countries whose wage is available in IALS. we cannot have sufficient plots. However, at face value, there is very little correlation between the two changes, doubting the previously raised point that higher return to skills worsen wage inequality.

3.2 Composition: distribution of cognitive skills and wage inequality

Here, the focus is on the distribution of cognitive skills and its relationship to wage inequality. A central question here is ”Do countries with higher literacy inequality exhibit higher wage inequality as well?”.

Figure 9 shows a cross-country relationship between log of percentile ratio of log hourly wage and that of literacy scores. Thus, the interpretation becomes an elasticity. For all of P90/P10, P90/P50 and P50/P10, a positive association can be found between the two. For example, the 90-10 percentile ratio of literacy increase by 1% is associated with 6% increase in 90-10 percentile ratio hourly wage. R^2 is also high, especially for inequalities involving 90 percentiles[20].

[20]Note that the distribution of cognitive skills calculated here correlates with that of years of education, which is not controlled for here. Thus, the real positive relationship is expected to be smaller than shown in the graph

Figure 10 shows the same for PIAAC in 2012. The relationship is somewhat weaker than before. In all of three inequality measures, R^2 has dropped. However, the coefficient associating the two inequality has risen for all. For example, 1% change in 50-10 literacy ratio is associated with 15% point rise in 50-10 wage ratio.

Figure 11 shows a correlation between the change in wage inequality and the change in literacy inequality. This is less vulnerable to ommited variable biases arising from country-fixed characteristics. Interestingly, the relationship is positive and strong for all the inequality measures. For example, a 1% change over time in ratio of 90-10 literacy ratio is associated with 3.8% increase in ratio 90-10 wage ratio[21]. Also R^2 is also high. From this, once we consider a time dimension, there seems a possibility that the rise of wage inequality is due partially to the rise of literacy inequality.

[21]This interpretation comes from that the coefficinet (= 3.8) connects $log(r^{lit}_{2012}) - log(r^{lit}_{1994}) = log(r^{lit}_{2012}/r^{lit}_{1994})$ with $log(r^{wage}_{2012}) - log(r^{wage}_{1994}) = log(r^{wage}_{2012}/r^{wage}_{1994})$, where r represents (any) percentile ratio.

4 Variance Decomposition

We have seen that, from the cross-country analysis, there is a possibility that literacy has shaped wage inequality through price effect and composition effect. This section investigates such hypothesis more formally by variance decomposition methods and tries to measure how much of the wage inequality change has been caused by these effects in each country.

As said previously, I study the change in wage inequality of 6 countries for which the continuous wage data was available for both IALS and PIAAC. Those countries are: Czech Republic, Denmark, Finland, Italy, Norway and Slovenia[22].

4.1 Literature review

Before moving to the variance decomposition analysis, this subsection introduces some works that are relevant to this paper in terms of research question and methodology[23].

Separating the effect of skills on wage inequality into price effect and composition effect, as will be done in this paper, is not new. Juhn et al. (1993), JMP hereafter, has applied a decomposition named ”full distribution accounting method” to the March Current Population Survey, to examine the extent to which the change in wage inequality in the US from the 1960s to the 1980s can be attributed to skill price effect, skill composition effect and residuals. They define skills as a set of education and work experience. A core idea of their decomposition is to regress wages on skills (i.e. education and experience) for each year, and calculate counterfactual wages if return to skills, distribution of skills and residuals respectively are distributed as in a different year. Their main finding is that residuals by far are the largest contributor of the risen inequality in the US, explaining almost two thirds of it; on the other hand, price effect have a moderate contribution and composition effect was negligible. From this observation, they conclude that the inequality has increased *within* narrowly defined skill groups, rather than between them. This points to a possible role of other skills that can increase inequality within the group of same education and experience.

Blau and Kahn (2005), BK hereafter, using IALS dataset, studies exactly this point. That is, they apply the same decomposition to examine the role of cognitive skills in explaining higher wage inequality in the US than other countries. They perform two decompositions: one that defines skill as only education and experience and the other that adds IALS scores into it. Then, they compare the results to see how much the addition of IALS scores alters the first decomposition result. It turns out that composition effect of cognitive skills plays only a minor role in explaining international differences of wage inequality, while price effect (of skills, including IALS score) and residuals play a larger role.

One major caveat of the decompostiion method used in these two papers, however, is that it can only decompose into three parts: ”total” price effect (price effect of all regressors combined), ”total” composition effect (compostion effect of all regressors combined) and

[22]Chile is removed from the analysis, as there are many flaws in the wage data that leaves the wage inequality measures suspicious.

[23]Detailed discussion on different decomposition techniques will be provided later, rather than here.

residuals. In other words, it does not show a relative contribution of each regressor[24]. Furthermore, the method uses simple OLS regressions which assume that return to skills does not vary among workers. This will lead to putting a lot of price factor into residuals, if return to skills is actually variant.

Autor et al. (2005), AKK hereafter, overcomes this problem. They employ a decomposition method involving a quantile regression, which was initially proposed by Machado and Mata (2005), MM hereafter, and is going to be used in this paper's analysis later, too. A detailed explanation of this methodology will be provided in the next subsection. AKK uses this method to study the rise in inequality in the US from 1973 to 2004. Likewise JMP, they use only education and experience. Their main finding is that skill composition played only a minor role for the overall evolution of inequality, in contrast to price effect which increased the upper-tail inequality throughout the entirety of the studied period, however affecting the lower-tale inequality in both positive and negative directions depending on period. Overall, price effect plays a bigger role than composition effect. They do not focus much on each variable's effect, nonetheless, despite that the methodology allows them to do so.

Paccagnella (2015), using PIAAC, extends AKK by introducing cognitive skills (numeracy). It employs unconditional quantile regression approach, proposed by Firpo, Fortin, and Lemieux (2009), to perform detailed decomposition analysis on international differences in wage inequality. The finding is zero or slightly negative composition effect of numeracy, positive price effect of numeracy for lower-tail inequality differences, and negative one for upper-tail inequality differences. However, the magnitude is small and education plays much larger role than numeracy.

I am also going to extend AKK by introducing cognitive skills, but perform a different analysis than Paccagnella (2015) in two ways: first, analysis is applied to inequalty change *within* a given country over time (i.e. from 1994 to 2012); second, I employ the MM decomposition (as used in AKK) rather than unconditional quantile regression, because it has a better advantage in analyzing comopsition effect[25].

This work will contribute to the literature in several ways. First, it reveals the role of cognitive skills in shaping the wage inequalities *over time*, which is yet studied using IALS and PIAAC dataset to the best of my knowledge. Second, by decomposing price effect and composition effect further into each variables, it uncovers relative importance of different skills in changing inequality landscape. In particular, it examines if the notion of edcuation as a factor of increasing wage inequality is due purely to the edcuation or partially to the distribution of underlying cognitive skills. Third, by studying more than one country, it shows whether the relationship between skills and change in inequality is similar or diversed across countries. This helps us understand a role of globalization as well as domestic market structure and institutions.

[24] BK does attempt to identify it by comparing two decomposition results. Yet, this is a rather indirect approach and does not fully account a portion of the change caused by a particular variable.

[25] It will be explained later in the chapter

4.2 Methodology: MM decomposition

As said before, this paper is an extension of AKK, which uses conditional quantile regressions for detailed decomposition analysis, originally proposed by Machado and Mata (2005). This subsection explains the methodology, and its advantage over other decomposition techniques.

The decomposition constitutes of three steps; first, use of conditional quantile regressions to estimate a set of coefficients across the (conditional) wage distribution of a given period; second, simulation of actual and counterfactual marginal wage densities, from a set of coefficients estimated and regressors in the data; third, decomposition of the wage inequality changes over time into each variable's price and composition effects, using a number of marginal densities calculated.

First step: conditional quantile regression

First step is to estimate a set of coefficients using conditional quantile regressions for each given year (i.e. 1994 and 2012). These coefficients will later allow one to fully characterize wage densities as well as counterfactual densities necessary for decomposition.

Let $Q_\theta(w|x)$ for $\theta \in (0,1)$ denote the θth quantile of the log hourly wage w given a vector x of covariates. In this analysis, x include literacy/numeracy scores, years of education, experience and its squared. The model for quantile regression is given by the conditional (linear) quantile function:

$$Q_\theta(w|x) = x'\beta(\theta) \tag{1}$$

where $\beta(\theta)$ is a vector of coefficients across quantiles (given x). $\beta(\theta)$ can be estimated through the following minimization problem:

$$\hat{\beta}(\theta) = \arg\min_{\beta \in \mathbb{R}} = \frac{1}{n}\sum_{i=1}^{n} \rho_\theta(w_i - x_i\beta)$$

where ρ_θ being the check function:

$$\rho_\theta(u) = \begin{cases} \theta u & \text{for } u >= 0 \\ (\theta - 1)u & \text{for } u <= 0 \end{cases}$$

Note that this approach is parametric in the sense that linearity in the equation (1) is an assumption, and the fit of the model affects the quality of simulations[26]. As said in MM, the conditional quantile process[27] can fully describe the conditional wage distribution. It is important to metion that $\beta(\theta)$ can capture wage variation of both "between" skill differences and "within" skill variaiton, in contrast to the OLS coefficient which accounts only for the "between" part.

[26] This type of specification holds, for example, for a location-scale model where location and scale are both a linear function of regressors, i.e. $w = \beta x + (\gamma x)\epsilon$.

[27] That is, $Q_\theta(w|x)$ as a function of θ.

Second step: wage simulation

Once the coefficients $\hat{\beta}(\theta)$ are estimated, it is possible to derive the marginal wage densities of wages. However, unlike OLS, it is not possible to directly "match" $\hat{\beta}(\theta)$ with x, because θ is not a quantile of x, but of w cnoditional on x. Using the probability integral transformation[28], if $\theta_1, \theta_2, ..., \theta_m$ are drawn randomly from a uniform distribution on the interval $(0, 1)$, then for given x_i, $\hat{w}_i = \{x_i'\hat{\beta}(\theta)\}_{i=1}^m$ will characterize a *conditional* distribution of wage given x_i. A full characterization of the marginal (or unconditional) distribution of w, on the other hand, requires to take into the account the joint density of covariates, $g(x)$. Thus, to simulate the marginal wage density of w, rows of data x_i are drawn randomly from $g(x)$, so are θ_i from a uniform distribution $(0, 1)$. These are then (randomly) matched so as to calculate $w_i = x_i\hat{\beta}(\theta_i)$. A set of w_i will characterzie the marginal wage distirbution implied by the quantile regression model.

For the purpose of decomposition, it is necessary to construct two marginal wage densities: one is (simulated) actual wage densities of a given period (i.e. 1994 and 2012), and the other is a set of counterfactual wage densities. Let $w(t)$ and $x(t)$ denote respectively the observed wages and covariates in period $t = 0, 1$, where $t = 0$ and $t = 1$ correspond to 1994 and 2012 respectively. Also denote $g(x; t)$ the joint density of covariates for time t. To simulate the actual wages, first I draw a random sample of size m, that is $\theta_1, \theta_2, ..., \theta_m$, from a uniform distribution of the interval $(0, 1)$. Then, I estimate $\hat{\beta}_t(\theta_i)$, a $k \times m$ matrix of coefficients, using quantile regression for each period. Next is to randomly draw with replacement $g_i(x; t)$ of size m from $g(x; t)$. As noted before, these information allow to calculate simulated actual wages:

$$\{\hat{w}_i(t) = g_i(x; t)'\hat{\beta}_t(\theta_i)\}_{i=1}^m$$

which has the following simulated wage densities:

$$f(\hat{w}(t)) = f(g(x; t), \hat{\beta}_t) \tag{2}$$

If the quantile regression specification is correct, this simulated wages will fully characterize the observed wage distributions in the data. In practice, follwoing Albrecht, Björklund, and Vroman (2003), instead of drawing m numbers of θ's at random, I simply assign quantiles from 1 to 99 with the interval of 0.2, i.e. $\theta_1 = 1, \theta_2 = 1.2, ..., \theta_{m-1} = 98.8, \theta_m = 99$. This gives in total 491 coefficients estimated across the (conditional) distribution of wage.

The decomposition uses a set of counterfactual distributions, i.e. the wage densities that would have prevailed at time t, if covariate(s) or coefficient(s) were like time t^*. Counterfactual wages at time t that could have prevailed if all covariates are distributed as time t^* can be given by $\{\hat{w}(t; g(t^*)) = g_i(t^*)'\hat{\beta}_t(\theta_i)\}_{i=1}^m$, which has the following density:

$$f(\hat{w}_i(t; g(x; t^*))) = f(g(x; t^*), \hat{\beta}_t) \tag{3}$$

[28]The theorem states that if X is a continuous random variable with cdf $F_X(X)$ and if $U = F_X(X)$, then U is a uniform random variable on the interval $[0, 1]$. In other words, if U is a random variable on the interval $[0, 1]$, then $F_X^{-1}(U)$ has the distribution of F_X.

It is straightforward to derive counterfactual wages of time t when all coefficients are of t^*, i.e. $\{\hat{w}(t;\beta_{t^*}) = g_i(t)'\hat{\beta}_{t^*}(\theta_i)\}_{i=1}^m$, with the density:

$$f(\hat{w}_i(t;\beta_{t^*})) = f(g(x;t^*),\hat{\beta}_{t^*}) \tag{4}$$

What is useful about this decomposition is that it can further divide composition and price effect into its sub-components. With regard to price effect, Studying it only requires to apply the coefficient of the corresponding quantile θ from a different time period. On the other hand, composition effect is slightly more complicated. If one wants to study the composition effect of a particular covariate, say χ in x, it requires to simulate the counterfactual wage density at time t that would look like if χ was distributed as in t^* (but keeping other covariates distributed as t). To do so, MM proposes to reweight the estimated wage at t, i.e. $\hat{w}(t)$, by the frequency distribution of χ at time t^*, through resampling with replacement[29]. However, this methodology cannot isolate an impact of a particular variable's effect, as reweighting also alters a distribution of other covariates. Thus, instead, I replace each value of $\chi(t)$ with the corresponding value of $\chi(t^*)$ based on an unconditional rank in in each distribution[30]. This is basically swapping the distribution of (only) a variable of interest between two periods, according to the relative rank in each distribution[31]. Then, I calculate a set of coutnerfacutal wages similarly as before.

An important assumption made in the construction of counterfacual wage densities is partial equilibrium framework, i.e. it is assumed that the change in composition does *not* affect the coefficient, and vice versa. This is not desirable from theoretical point of view because (relative) supply of skills might affect the price of skills too (e.g. the less there is workers with higher education, the higher premium of higher education is, should demand remain unchanged). This is an important limitation of this decomposition, although this is a common problem among decompositions of similar kind. More detailed discussion will follow later with a mention of papers that overcome this partial equilibrium problem.

Third step: decomposition

The purpose of decomposition is to quantify a contribution of each variable, through price and composition effect, on the overall change in wage inequality from 1994 to 2012. With all simulated actual and counterfacual wage densities described above, it is possible to perform such analysis. Denote $f(w(t))$ and $f(\hat{w}(t))$ respectively the actual and the simulated actual wage densities at time t. Similarly, let $f(\hat{w}(t;g(t^*)))$ be the wage densities that would have prevailed if all covariates are distributed as in t^* period[32]. Let $R(.)$ be inequality statistics,

[29]As in their example, if one wishes to study the effect of gender distribution, one needs to randomly draw with replacement a number of male subsamples proportional to the ratio of male at time t^*, and do the same for female. In the case of a continuous variable, they suggest to partition it into J classifications based on frequency distribution.

[30]For example, I replace the 200th value of $\chi(t)$ with the 200th value of $\chi(t^*)$

[31]However, this is not provide a perfectly consistent estimate, as it cannot fully take into the account a joint distribution $g(x;t)$ in assigning new values. In other words, the use of unconditional rank amounts to making an assumption that the correlations among covariates are same between 1994 and 2012.

[32]Simplifying $g(x;t^*)$ to $g(x;t^*)$

such as P90/P50. With these notations, the change in inequality statistics R from 1994 to 2012 can be decomposed in the following way:

$$\begin{aligned} R(f(w(1))) - R(f(w(0))) &= R(f(\hat{w}(1))) - R(f(\hat{w}(0))) + residual \\ &= R(f(\hat{w}(1; g(0)))) - R(f(\hat{w}(0))) \\ &\quad + R(f(\hat{w}(1))) - R(f(\hat{w}(1; g(0)))) \\ &\quad + residual \\ &= TPE + TCE + residual \end{aligned} \tag{5}$$

where TPE and TCE stand respectively for total price effect and for total composition effect, i.e. changes in inequality statistics due to the difference, between 2012 and 1994, in coefficieints of all covariates and due to the difference in composition of all covariates. Residual is a simulation error, that is the difference in inequality statistics between actual and simulated actual densities.

In addition, write $f(\hat{w}(t; \beta_{t^*}^{\chi})$ the wage density that would have prevailed at time t if (only) a coefficient of χ was of time t^*. Then, based on the equation (5), individual IPE (individual price effect), a contribution of each regressor through price effect, is given by:

$$IPE = R(f(\hat{w}(0; \beta_1^{\chi}))) - R(f(\hat{w}(0))) \tag{6}$$

Similarly, let $f(\hat{w}(t; \chi(t^*))$ denote the counterfactual wage density of time t if (only) a covariate χ is distributed as in t^*. Again, based on the equation (5), the individual contribution of variable χ through price effect, i.e. ICE (individual price effect) can be derived by:

$$ICE = R(f(\hat{w}(1))) - R(f(\hat{w}(1; \chi(0))) \tag{7}$$

Notice that the MM decomposition method is very similar to the standard Oaxaca-Blinder decomposition, except for several features. First, instead of mean difference between two groups (periods), it can study difference in inequality statistics, i.e. $R(.)$, thanks to a number of wage densities simulated. Furthermore the MM decomposition can reflect difference in entire distribution of covariate(s), rather than only mean difference of covariate(s). Similarly it also allows a varying β's, which captures not only between skill but also within skill variation in wages, compared to the Oaxaca-Blinder decomposition. On the other hand, the MM shares a weakness with Oxaca-Blinder in that *order* of decomposition matters. That is, instead of equation (5), the decomposition could go in the following way:

$$\begin{aligned} R(f(w(1))) - R(f(w(0))) &= R(f(\hat{w}(1))) - R(f(\hat{w}(0))) + residual \\ &= R(f(\hat{w}(1))) - R(f(\hat{w}(0; g(1)))) \\ &\quad + R(f(\hat{w}(0; g(1)))) - R(f(\hat{w}(0))) \\ &\quad + residual \\ &= TPE + TCE + residual \end{aligned} \tag{8}$$

With this order of decomposition, the calculation of IPE and ICE also alters. For this reason, decomposition results of an alternative order is also presented in the appendix. The results looks generally similar.

Since the simulation result depends on a random draw of $\{g_i(x;t)\}_{i=1}^m$ from $g(x;t)$, I perform this the decomposition analysis using 50 simulated actual and counterfacual wages calculated based on a different draw of $\{g_i(x;t)\}_{i=1}^m$. I report only the mean result with standard deviation when presenting the decomposition results below.

Comparison to other decomposition techniques

There are a number of decomposition techniques used for inequalities. I briefly introduce other methods and explain why MM decomposition is the most appropriate for this paper.

Perhaps the most famous is Oaxaca-Blinder decomposition. It decomposes a mean difference between two groups into difference in coefficient and difference in average characteristics. DFL decomposition proposed by DiNardo et al. (1996) is a generalization of Oaxaca-Blinder decomposition and it uses reweighting of kernel density distribution to enable a decomposition of difference between two groups at any point of distribution (as opposed to only mean in Oaxaca-Blinder decomposition). It is regarded as a very elegant approach as it imposes few parametric assumptions. It is not, however, suited for studying price effect and also relies on partial equilibrium framework (i.e. assumes that composition does not affect price). JMP's "full distribution accounting method" also studies an entire distribution and moreoever allows one to isolate three parts: price effect, composition effect and residuals. It forms on a construction of counterfactual wages based on a simple OLS regression separately run for each group. A weakness of this methodology is that it imposes a strong assumptino on the behavior of residuals and more importantly three components do not add up to the actual observed inequality. It relies on a partial equilibrium model, too. As said before, MM decomposition employs conditional quantile regression (CQR) which allows a detailed decomposition of price effect and composition effect. Furthermore, as done in AKK, it enables one separate price effect into between-group and within-group price effect, which constitute a part in discussion of the results. Unlike JMP, price and composition effect add up to total, if the specification is correct. It is, nonetheless, a parametric approach (due to the use of conditional quantile regression) and relies on a partial equilibrium framework. Being computationally demanding is an additional disadvantage. The last method is unconditional quantile regression (UQR) method, proposed by Firpo et al. (2009). It uses a RIF (recentered influence function) to directly estimate an impact of particular variable on a quantile value of interest. Unlike conditional quantile regressions, this method provides coefficients that are interpretable as a marginal effect on a distribution of wages (i.e. not conditional on X). Decomposition of inequality measures is also possible in this approach, applying a simple Oaxaca-Blinder type decomposition at different point of distribution. It, however, imposes a restrictive parametric assumptions in the estimation of coefficient.

It is clear that MM approach is more useful than the method of Oaxaca-Blinder, DFL and JMP, as it allows a detailed decomposition essential for understanding the contribution of cognitive skills to the wage inequality evolution. This can be done, nevertheless, by UQR method as well and indeed it has more desirable features than CQR used in MM. However, I use MM decomposition for several reasons. First, I am able to compare the results to AKK, which uses MM decomposition, and see how the addition of cognitive skills in estimation changes relative contribution of cognitive skills and educaiton. Second, MM method characterizes an entire distribution of counterfactuals, thus marginal effect of a variable of interest on an entire wage distribution becomes graphically visible, in contrast to UQR which can only estimate marginal effects. Thirdly, as said in Fortin, Lemieux, and Firpo (2011), MM is a natural way of decomposition a price effect and, as AKK does, it can explicitly discusses between-skill and within-skill price effect. CQR estimate quantile coefficients that takes into the account the both between-skill and within-skill price effect at once, and it is one of major advantage of UQR. However, a separation of these two effects also gives an insight, as shown later in discussing the results.

4.3 Results

This section presents results of the decomposition. I present two different types of analysis. First is the one described in the previous section, that is the decomposition of the change in wage inequality into different effects. Second is the marginal effects analysis that display more clearly each variable's effect by showing how much the wage inequality in 2012 would change if price/composition is of 1994. These two are essentially same apart from the mode of documentation, however.

Decomposition

Mincer model
As a becnhmark, I present the result of decomposition analysis of Mincer model that uses only education, experience and squared experience in Table 10. It is later compared to the results of Complete model which adds literacy. For each country and for change in each inequality measure, the tables show actual inequality, simulated actual inequality (from equation (2)), price effects, composition effects and residual. Each entry in price effects and composition effects shows the contribution of each variable. Except the actual inequalities, all values are mean of 50 simulations with standard deviation in bracket.

Looking at Table 10, it seems that simulated wage inequality does not quite approximate to the actual wage inequality, being smaller than the actual values. It implies that the overall fit of the quantile regression was not particularly good and there are a large unexplained portion of the wage inequality change under this specification. The discprepancy is especially high for the change in P90/P10 but less so for the changes in other ratios and coefficient of variation. The simulation looks better for Finland and Norway than other countries.

Having said that, it seems price effect is usually larger in magnitude than composition effect. For example, total price effect for the change in P90/P10 in Finland is 0.12, as compared to 0.03 of total composition effect. This is consistent with the result found in JMP and AKK for the US, so is with other works on international differences, including BK and Paccagnella (2015). The same argument holds for individual price effect of education and experience. Except Czech and Italy, price effect of education is positive, meaning that the change in return to edcuation has increased wage inequality over time. This is contrasted to the negative effect of education's composition effect. It is interesting to see generally positive effect of experience both for price and composition, and it is large in magnitude than education. The findings here about composition effect is very different from MM that studies Portuguese wage inequality between 1986 and 1995. While they found a positive effect of education composition and little effect of experience composition, the findings here suggest that composition of education rather decreases inequality and that of experience unequivocally increases inequality, remarkably for all the studied countries. This might imply the shift of market structure since early 1990s until the recent years.

Note that the effect of constant term is sizable. It is not straightforward to interpret this and few papers that employ MM decomposition actually mention the role of constant term, to the best of my knowledge. In theory, constant term in a quantile regression reflects the way a base wage, irrespective of covariates, is distributed. Thus, in a way, it might constitute a part of unexplained effects that also influence change wage inequality.

Complete model

The main interest of this paper is the effect of cognitive skills on the wage inequality changes. Table 11 presents the results of decomposition for Complete model. General observation on simulated wage inequality, total price effect and total composition effect is very similar to the previous model. Residual slightly decreases in general by introducing literacy in the model. It is also the same that price effects dominate composition effects.

Focusing on literacy in particular, there is virtually no composition effect in all countries. It seems, therefore, that a cross-sectional association of literacy distribution and wage inequality shown in the previuos section is either false or true only between countries. At least, over time within a country, increase in dispersion of literacy skills does not have a visible impact on wage inequality. In opposition, literacy's price effect is generally far from zero and positive, with the exceptions of Czech and Italy which have a negative sign. Magnitude of literacy's price effect is respectable and it generally exceeds that of education.

Another interesting exercise is to compare the effect of education in Complete model to the one from the previous Mincer model. By adding literacy in the equation, price effect of education decreases respectably. For example, price effect of literacy in Denmark and in Finland is 0.42 and 0.25 for the change in P90/P10 for Mincer model, but these have decreased to 0.18 and 0.14 respectively by adding literacy in the equaiton. Composition effect of education decreases, too. Given that residual does not decrese so much even after including literacy, it seems that cognitive skills have simply taken away a part of education that contributes to the change in inequality.

AKK has shown that price effect of education is largely responsible for the rising wage inequality in the US since 1970s. The finding of this paper indicates that such role of education may partially come from the price effect of literacy.

Researchers have considered a possibility that a rise of return to education in recent decades reflects a shift of labor demand to relatively high skilled individuals. Supposing that measured literacy can, at least partially, measure the abitliy to perform such high-skilled jobs, the fact that literacy price has increased wage inequality in many countries is consistent with such skill demand argument.

Marginal effect

To grasp more easily the effect of each variable's price and composition effect, I also present the result of marginal effect analysis. This shows "how much will the wage inequality in 2012 change, if price/composition of a particular variable was of 1994?". As before, the results for both Mincer model and Complete model are presented, respectively in Table 12 and in Table 13. Each entry of the table should be read as how much the inequality measure in 2012 changes if a variable's price/composition is of 1994. Thus, a positive (negative) sign means that the actual wage has decrased (incrased) due to that variable. For example, in Czech, P90/P10 could have been 0.92 higher if education's price was like 1994. In reverse, it means that, in reality, education has *lowered* the wage inequality by that much.

In both tables, the simulated inequalty measures in 2012 look quite approximate to the actual ones. This confirms that wage simulation is actually not as bad as the impression from the previous tables. A large discrepancies observed in the previous decomposition seems to stem from the combination of two small errors in both periods.

General results are (of course) in line with the previous decomposition results. Again, price effects dominate composition effect in total and for each variable. From the Mincer model results, inequalities could have been lower if the price on education and experience remained as of 1994. On the other hand, it could have been larger if literacy were distributed as in 1994. From the result of Complete model, literacy barely changes the 2012 inequality, even if it is distributed as in 1994. On the contrary, except Czech and Italy, the inequality could have been smaller if return to literacy remained similar to that in 1994.

Figure **??** visualizes the entire distributions of simulated 2012 actual wages (normal line), of counterfactual 2012 wages with 1994 literacy distribution (dashed line) and of counterfactual 2012 wages with 1994 literacy coefficient. As seen, a normal line and a dashed line are very similar in all the countries, indicating little composition effect of literacy. On the other hand, dotted line departs a lot from the simulated actual wages.

Summary of results

In sum, there are several notable findings from the decomposition analysis:

- Overall, price effects deminate composition effects

- Literacy does explain a part of the changing inequality, and its effect comes mostly from price effect. In 4 out of the 6 countries studied, literacy's price effect increased the wage inequality and its relative contribution is often larger than education. On the other hand, there is virtually no composition effect of literacy.

- Even after controlling for literacy, education still increases wage inequality through price effect, which is partially offset by negative effect of composition.

- Education's contribution (both price and composition effect) falls, once literacy is added in the specification.

Caution must be taken, nonetheless, that there is a variation across countries and across inequality measures in terms of signs of effects and magnitude. It is worth mentioning, too, that a fair part of wage inequality changes remain unexplained as a result of decomposition.

4.4 Discussion

Comparison to previous literature

The decomposition analysis has shown a number of findings. How do they square with the previous literature? To begin, it must be said that it is difficult to compare due to a large variation in studied period, country and used methodology. Nonetheless, it is still interesting to make a comparison.

The most common between this paper and previous work is much larger impact of price effects than composition effects. On the other hand, for contribution of each variable, I find somewhat different result. In particular, literacy's price effect being almost as large as education, unlike BK and Paccagnella (2015) that find much smaller contribution of cognitive skills relative to education. One major difference between them and this paper is the dimension of the difference studied: in their paper, the explained difference is "between countries at a given time", while my study here is "within a country at different time". Taken at face value, therefore, literacy matters more in wage inequality change over time than difference across countries. In addition, it might reflect a bias from a country-specific confounders in the process of their decomposition[33]. These, on the contrary, tend to be more rigid over time (as in well-known institutional inertia, for example), thus less likely cause a problem for within-country analysis. Positive price effect of education is in line with previous findings including BK, AKK and Paccagnella (2015). However, I find a generally negative (although weak) effect of education composition, regardless of the presence of literacy. This is in contrast with BK and AKK, however is less inconsistent with Paccagnella (2015) that finds a negative composition effect of education for some countries. This finding may partially reflect the view in MM that a rise in share of highly educated labor force reduces inequality, keeping price fixed.

Finally, fall of education's contribution after entering literacy in the equation is a new finding. This indicates that a large role of education's price effect using Mincer model (e.g. AKK for the US since 1970s till early 2000s) is partially explained by literacy's effect. Similarly, literacy can explain in part the rise of "within-skill" wage dispersion as suggested in JMP. Note, however, that this finding does *not* mean role of education is small, because literacy is strongly correlated with education level. Indeed, Carlsson et al. (2015) has recently showed a causal impact of schooling on cognitive skills in Sweden. Thus, to the extent that education causally increase wages, education remains still an important factor, especially as a

[33]For example, social behavior is an important determinant of wages in some countries, whereas it is not in others. Assuming that education is correlated with social behavior in all countries, the omission of such behavioral factor from the regression will overstate the role of education in some country than in the others, making cognitive skills look relatively unimportant. This does not happen in within a country, if the market values behavior in the same way in both periods.

policy instrument.

Detailed investgation on literay's effect

Since this paper's main objective is to examine the role of literacy in explaining the change in wage inequality, which turned out to be positive in 4 out of 6 countries, it is useful to investigate it in more detail. To better understand how literacy's price effect increased wage inequality in some countries, while not in other countries, Figure 11 compares the quantile coefficients of literacy between 1994 and 2012. For the sake of comparison, coefficient is expressed as elasticity. It seems that in Czech and Italy, the countries that exhibit negative price effect of literacy, return to literacy has become a decreasing function of (conditional) wage quantile in 2012, in comparison to the flat return in 1994. However, OLS return has risen over time. This means that, in these countries, literacy price has increased inequality "between" literacy groups (i.e. between people with low literacy and high literacy), but compressed wage inequality "within" a literacy group. On the other hand, in other countries, the story is more mixed. In Finland, it was the change in "within" literacy price that increased wage inequality, whereas it is "between" literacy price in Norway. It looks a combination of both in Slovenia and Denmark. In any cases, what is clear from the figures is that in 1994 return to literacy was relatively flat across the quantile, but it has gone through a large transition since then. Average return to literacy has risen in many countries (except Finland) and moreover has changed its distribution across conditional quantiles.

An interesting comparison can be made to the quantile coefficients of education (in Complete model), shown in Figure 11. What is notable is the sharp rise of "between" education price effect (i.e. OLS coefficient) in contrast to the little change in "within" education price effect (i.e. the distribution of coefficients). Hence, education's contribution to the rise of inequality through price effect seems almost entirely driven by a stable rise of return across the entire wage distribution, but not to the change in return within an education group[34].

In sum, though both "between" return to literacy and education increased in many countries, it was only literacy that experienced the change in "within" return. In other words, return to education is generally inequality enhancing (given an increasing return on condtional quantile), but such feature has netiher weakened or strenghened over time. On the other hand, return to cognitive skill was not so inequality-enhancing in 1994. However, it has become so by increasing a general return to cognitive skills, which was either strengthened or weakened by the chaning distribution of the return, depending on countries.

By a side note, Martins and Pereira (2004) finds return to education that is increasing in conditional quantile in many European countries in the mid-1990s and suggests a possible role of unmeasured ability interacting with education[35]. This "ability" that cannot be measured by edcuation may be cognitive skills. As far as Figure 11 is concerned, however, education's increasing return in conditional wage quantile does disappear for many countries. Thus, it is

[34]Rising between skill return is probably due to the economic growth.

[35]There is ability that raises wage and it is correlated with education. Then, as said in the paper, "This would mean that the role of ability differences within a given schooling level would become increasingly amplified in terms of pay as one considers high schooling levels".

not likely basic cognitive skills that explain education's feature of enhancing inequality.

What explains the evolution of return to literacy and its contribution to wage inequality between 1994 and 2012? That is certainly a question for future research, but there are some works that are possibly relevant in explaining it. To begin, as seen in Table 2, average cognitive skills scores have not changed much over time. Inequality in cognitive skills has increased in many countries, but not at all drastically. It, thus, seems necessary to look beyond skill supply side. In this sense, SBTC is still an appealing theory, especially the rising return to literacy between literacy groups (i.e. OLS). It is also possible that SBTC has increased within-literacy-group inequality if literacy is more awarded at the top of wage distribution. It is difficult, however, for SBTC alone to explain fully the transition of literacy return distribution, because 4 out of 6 countries did not see such rise in return at the top of wage distribution. Beaudry, Green, and Sand (2016) has recently found an interesting reversal in demand for cognitive tasks. According to them, in the US since 2000, demand for jobs that require high cognitive skills have declined, following a slowdown of the boom in investment in high-tech jobs. This pushed high-skilled individual lower in the occupational ladder, affecting lower skilled workers negatively too. If such phenomenon is true, depending on how it transformed labor demand for a given level of literacy, it could help explain a varying shape of distribution across countries in 2012. In addition to these explanations, other factors such as higher level cognitive skills not captured by IALS or PIAAC, majors at college (Altonji, Kahn, and Speer (2014), for example), firm-specific skills and so on would have been relevant, too. Further investigation is necessary to uncover the reason behind a varying evolutions of cognitive skill return across countries.

5 Conclusion

Throughout the paper, I have investigated a role of cognitive skills in explaining the evolution of wage inequality since 1994 until 2012. I first studied a cross-country relationship between return to cognitive skills and wage inequality, as well as between cognitive skill inequality and wage inequality. Both in 1994 and in 2012, these relationship turns out to generally be positive. However, once I do a difference-in-difference (between two periods and between countries), such positive relationship between return to literacy and wage inequality has disappeared. On the other hand, the positive relation between cognitive skill inequality has remained positive particularly for lower tail inequalities (i.e. P50/P10).

Then, I performed a detailed decomposition analysis of the wage inequality evolution for 6 country each, usign conditional quantile regressions. I find that literacy has increased wage inequality in 2 out of 6 countries through price effect, but no composition effect. This is contrary to the observation in the previous macro-level analysis. Education also increased inequality through price effect, which is partially offset by a negative composition effect. Relative contribution of literacy is found as large as that of edcuation, which is counteracting to the findings in previous literature. Once literacy is controlled for, relative contribution of education drops, indicating that a part of edcuation's impact on inequality documented in a number of previous works is, at least in part, due to literacy.

Literacy's price effect reflects both between-literacy effect and withi-literacy effect. In most of the countries, price of literacy has increased inequality between different literacy-level groups. However, within a group, return to literacy has become inequaliy-enhacning in some countries (e.g. Finland), whereas in other countries it became inequality-compressing (e.g. Italy). This change in the dispersion of within-group price effect is particular to literacy and is not observed in the case of educaiton. This raises a question on the cause of such change. SBTC seem relevant, but it alone cannot explain the cross-country variation. A recent reversal in skill demand might help one explain, but other factors cannot be ruled out. This calls for a future analysis, perhaps including more countries in the analysis, to fully understand the evolution of the wage inequality and the role of cognitive skills in explaining it.

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Appendices

A Macro analysis using OECD data

This appendix section shows the result of cross-country analysis using OECD data. It seems that the positive relationship found previously usign IALS and PIAAC data are not strong and sometimes even negative for this data. Note that this OECD data is not wage ienquality; it uses earnings inequaliy for 1994 and income inequaltiy in 2012.

B Result of variance decomposition in reverse order

Here presents the results of variance decomposition in reverse order, specified in the equation 8.

C Results using numeracy

This section presents a number of tables and figures that use numeracy score instead of literacy one. Note that, according to OECD (2016), quantitative literacy in IALS and numeracy in PIAAC are not comparable measures. Yet, overall, the results are similar to literacy.

Tables

Table 1: Descritption of IALS and PIAAC surveys

	IALS (International Adult Literacy Survey)	PIAAC (the Survey of Adult Skills)
Period of administration	1994-1998	2012, 2014
Participating countries / regions	22 (Belgium, Canada (English, French), Chile, Czech Republic, Denmark, Finland, Germany, Great Britain, Hungary, Ireland, Italy, Newtherlands, New Zealand, Northern Ireland, Norway, Poland,,Slovenia, Sweden, Switzerland (French, German, Italian), United States	24 + 9 (Round 1: Australia, Austria, Belgium (Flanders), Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russia, Slovak Republic, Spain, Sweden, UK (England and Northern Ireland), United States. Round 2: Chile, Greece, Indonesia, Israel, Lithuania, New Zealand, Singapore, Slovenia, Turkey)
Sample size	1500 - 6000	5000 - 27000
Domain of skills	Prose literacy, Document literacy, Quantatitive literacy	Literacy (Prose literacy and Document literacy combined), Numeracy, Problem solving in technology-rich environments
Mode of delivery	Paper-based	Computer-based (with an option of paper-and-pencil for those unfamiliar with computers)
Score range	0 - 500	0 - 500

Table 2: Distribution of literacy skills by country

Country	N	Mean	C.V.	Percentile P90	Percentile P50	Percentile P10	Ratio P90/P10	Ratio P90/P50	Ratio P50/P10
				IALS94					
Belgium	584	290.9	0.14	336.9	296.8	238.7	1.41	1.14	1.24
Canada	1158	281.6	0.18	339.3	288.3	215.4	1.58	1.18	1.34
Chile	584	230.7	0.20	290.3	233.2	169.1	1.72	1.24	1.38
Czech	526	287.2	0.13	329.9	290.6	239.2	1.38	1.14	1.21
Denmark	971	294.1	0.12	333.4	298.0	247.1	1.35	1.12	1.21
Finland	603	293.1	0.13	338.8	296.5	244.4	1.39	1.14	1.21
Germany	581	286.1	0.14	337.9	286.4	237.8	1.42	1.18	1.20
Hungary	518	252.9	0.15	296.9	260.1	197.0	1.51	1.14	1.32
Ireland	654	269.6	0.19	325.9	277.2	207.1	1.57	1.18	1.34
Italy	650	259.0	0.18	309.1	267.5	195.4	1.58	1.16	1.37
Netherlands	1009	293.0	0.13	335.1	298.5	245.0	1.37	1.12	1.22
Newzealand	1018	286.2	0.15	338.6	290.3	229.1	1.48	1.17	1.27
Norway	884	301.2	0.12	343.8	308.4	249.7	1.38	1.11	1.23
Poland	785	235.2	0.23	301.3	241.6	147.7	2.04	1.25	1.64
Slovenia	495	233.3	0.21	292.5	239.0	154.1	1.90	1.22	1.55
Sweden	848	308.2	0.14	361.4	312.0	254.3	1.42	1.16	1.23
UK	2070	281.0	0.18	337.7	287.5	215.6	1.57	1.17	1.33
USA	997	271.7	0.22	339.2	283.4	181.9	1.86	1.20	1.56
Average	802	275.3	0.16	327.1	280.8	214.9	1.55	1.17	1.33
				PIAAC12					
Austria	2302	274.3	0.15	325.1	278.3	220.6	1.47	1.17	1.26
Belgium	2277	277.0	0.16	331.4	283.2	215.2	1.54	1.17	1.32
Canada	11621	268.1	0.18	327.4	272.4	204.5	1.60	1.20	1.33
Chile	2008	223.1	0.23	289.3	223.5	158.4	1.83	1.29	1.41
Cyprus	1604	269.3	0.14	317.1	272.7	218.8	1.45	1.16	1.25
Czech	2539	277.8	0.14	324.7	281.9	226.7	1.43	1.15	1.24
Denmark	3279	268.2	0.18	323.3	275.1	205.8	1.57	1.18	1.34
Estonia	3144	274.2	0.16	325.1	277.9	216.8	1.50	1.17	1.28
Finland	2521	288.4	0.16	345.0	292.3	226.6	1.52	1.18	1.29
France	3074	262.9	0.18	320.3	267.1	200.4	1.60	1.20	1.33
Germany	2464	275.4	0.16	329.6	279.6	215.2	1.53	1.18	1.30
Greece	2031	249.0	0.16	300.3	248.9	199.7	1.50	1.21	1.25
Ireland	2501	269.7	0.17	324.3	273.8	211.1	1.54	1.18	1.30
Israel	2474	248.9	0.22	314.3	253.5	181.1	1.74	1.24	1.40
Italy	2022	254.5	0.17	308.8	256.5	198.4	1.56	1.20	1.29
Japan	2264	298.7	0.12	341.1	303.6	248.8	1.37	1.12	1.22
Korea	2849	274.7	0.14	320.6	278.4	224.3	1.43	1.15	1.24
Lithuania	1836	264.1	0.14	313.2	265.8	215.5	1.45	1.18	1.23
Netherlands	2292	287.7	0.15	338.7	293.9	227.3	1.49	1.15	1.29
Newzealand	2393	278.2	0.17	333.1	282.8	216.6	1.54	1.18	1.31
Norway	2313	282.7	0.16	334.6	288.4	225.6	1.48	1.16	1.28
Poland	4352	270.8	0.17	324.7	274.4	211.0	1.54	1.18	1.30
Russia	1242	278.3	0.15	327.6	281.3	223.8	1.46	1.16	1.26
Singapore	2423	258.9	0.23	326.1	269.6	174.9	1.86	1.21	1.54
Slovakia	2467	272.4	0.14	317.1	276.7	222.5	1.42	1.15	1.24
Slovenia	2370	255.8	0.18	312.6	259.0	194.3	1.61	1.21	1.33
Spain	2721	251.7	0.20	311.7	255.3	185.3	1.68	1.22	1.38
Sweden	2111	283.3	0.18	339.9	289.4	221.1	1.54	1.17	1.31
Turkey	2444	233.1	0.16	279.3	235.1	182.1	1.53	1.19	1.29
UK	3385	273.0	0.17	332.3	276.0	211.1	1.57	1.20	1.31
USA	1942	269.6	0.17	327.5	271.9	204.9	1.60	1.20	1.33
Average	2750	268.2	0.17	322.1	272.2	209.3	1.55	1.18	1.30

Table 3: Distribution of numeracy skills by country

				Percentile			Ratio		
Country	N	Mean	C.V.	P90	P50	P10	P90/P10	P90/P50	P50/P10
				IALS94					
Belgium	584	305.3	0.17	363.1	310.5	240.6	1.51	1.17	1.29
Canada	1158	286.3	0.19	349.9	290.5	216.0	1.62	1.20	1.35
Chile	584	227.6	0.28	301.9	232.0	134.4	2.25	1.30	1.73
Czech	526	313.4	0.15	369.2	319.4	250.8	1.47	1.16	1.27
Denmark	971	311.4	0.13	358.2	315.8	260.7	1.37	1.13	1.21
Finland	603	298.6	0.13	346.6	302.0	250.8	1.38	1.15	1.20
Germany	581	299.8	0.14	351.7	300.4	243.1	1.45	1.17	1.24
Hungary	518	280.0	0.16	349.0	280.9	232.5	1.50	1.24	1.21
Ireland	654	276.7	0.22	343.4	285.1	195.1	1.76	1.20	1.46
Italy	650	271.2	0.20	327.4	281.3	200.3	1.64	1.16	1.40
Netherlands	1009	302.2	0.14	350.5	306.8	248.7	1.41	1.14	1.23
Newzealand	1018	293.4	0.17	354.3	299.0	230.8	1.54	1.18	1.30
Norway	884	311.2	0.13	360.3	315.4	255.8	1.41	1.14	1.23
Poland	785	245.0	0.27	321.5	256.5	139.7	2.30	1.25	1.84
Slovenia	495	247.5	0.26	320.7	258.3	147.3	2.18	1.24	1.75
Sweden	848	316.4	0.16	374.8	318.2	253.8	1.48	1.18	1.25
UK	2070	293.7	0.19	358.4	300.6	217.9	1.64	1.19	1.38
USA	997	281.3	0.25	361.9	293.6	177.5	2.04	1.23	1.65
Average	802	286.7	0.19	347.9	292.6	216.4	1.66	1.19	1.39
				PIAAC12					
Austria	2302	285.1	0.16	339.3	290.3	226.3	1.50	1.17	1.28
Belgium	2277	286.7	0.17	343.6	292.6	222.0	1.55	1.17	1.32
Canada	11621	264.4	0.21	330.6	269.1	193.5	1.71	1.23	1.39
Chile	2008	213.8	0.27	286.8	213.3	139.0	2.06	1.34	1.53
Cyprus	1604	268.3	0.17	322.5	272.1	211.4	1.53	1.19	1.29
Czech	2539	281.6	0.15	331.9	285.2	227.8	1.46	1.16	1.25
Denmark	3279	282.7	0.18	342.2	288.5	219.4	1.56	1.19	1.31
Estonia	3144	274.7	0.16	329.6	277.3	217.5	1.52	1.19	1.28
Finland	2521	290.0	0.17	348.4	294.0	228.3	1.53	1.19	1.29
France	3074	261.3	0.21	326.3	266.9	188.4	1.73	1.22	1.42
Germany	2464	283.0	0.17	340.4	288.4	217.8	1.56	1.18	1.32
Greece	2031	253.3	0.17	305.6	252.1	200.6	1.52	1.21	1.26
Ireland	2501	263.7	0.20	326.3	267.8	199.9	1.63	1.22	1.34
Israel	2474	249.6	0.25	325.5	254.8	167.0	1.95	1.28	1.53
Italy	2022	257.0	0.19	317.7	258.6	196.1	1.62	1.23	1.32
Japan	2264	295.7	0.14	344.8	299.8	240.1	1.44	1.15	1.25
Korea	2849	267.5	0.16	319.7	270.7	212.2	1.51	1.18	1.28
Lithuania	1836	266.1	0.17	321.6	266.1	211.9	1.52	1.21	1.26
Netherlands	2292	289.8	0.16	343.0	295.9	227.1	1.51	1.16	1.30
Newzealand	2393	274.0	0.20	339.5	278.7	202.7	1.68	1.22	1.37
Norway	2313	288.4	0.18	346.6	296.0	222.5	1.56	1.17	1.33
Poland	4352	265.5	0.18	325.5	268.6	203.3	1.60	1.21	1.32
Russia	1242	273.7	0.15	322.9	276.6	223.9	1.44	1.17	1.24
Singapore	2423	261.9	0.26	337.2	275.9	157.8	2.14	1.22	1.75
Slovakia	2467	275.3	0.16	328.0	280.5	216.0	1.52	1.17	1.30
Slovenia	2370	260.6	0.20	322.8	265.1	194.4	1.66	1.22	1.36
Spain	2721	249.1	0.21	311.0	254.0	179.0	1.74	1.22	1.42
Sweden	2111	288.6	0.19	349.7	296.0	222.2	1.57	1.18	1.33
Turkey	2444	234.1	0.20	291.4	237.1	173.8	1.68	1.23	1.36
UK	3385	267.5	0.20	333.5	271.1	199.1	1.68	1.23	1.36
USA	1942	259.0	0.20	323.6	261.7	188.0	1.72	1.24	1.39
Average	2750	268.8	0.19	328.3	273.1	204.2	1.62	1.20	1.35

Table 4: Literacy inequality by country

	P90/P10			P90/P50			P50/P10		
	Level		Change	Level		Change	Level		Change
Country	IALS94	PIAAC12	PIAAC12 - IALS94	IALS94	PIAAC12	PIAAC12 - IALS94	IALS94	PIAAC12	PIAAC12 - IALS94
Belgium	1.41	1.54	0.13	1.14	1.17	0.03	1.24	1.32	0.07
Canada	1.58	1.60	0.03	1.18	1.20	0.02	1.34	1.33	-0.01
Chile	1.72	1.83	0.11	1.24	1.29	0.05	1.38	1.41	0.03
Czech	1.38	1.43	0.05	1.14	1.15	0.02	1.22	1.24	0.03
Denmark	1.35	1.57	0.22	1.12	1.18	0.06	1.21	1.34	0.13
Finland	1.39	1.52	0.14	1.14	1.18	0.04	1.21	1.29	0.08
Germany	1.42	1.53	0.11	1.18	1.18	0.00	1.20	1.30	0.09
Ireland	1.57	1.54	-0.03	1.18	1.18	0.01	1.34	1.30	-0.04
Italy	1.58	1.56	-0.02	1.15	1.20	0.05	1.37	1.29	-0.08
Netherlands	1.37	1.49	0.12	1.12	1.15	0.03	1.22	1.29	0.07
Newzealand	1.48	1.54	0.07	1.17	1.18	0.01	1.27	1.31	0.04
Norway	1.37	1.49	0.11	1.11	1.16	0.05	1.23	1.28	0.05
Poland	2.04	1.54	-0.50	1.25	1.18	-0.06	1.64	1.30	-0.33
Slovenia	1.89	1.61	-0.29	1.22	1.21	-0.01	1.55	1.33	-0.22
Sweden	1.42	1.54	0.12	1.16	1.17	0.02	1.23	1.31	0.08
UK	1.57	1.58	0.01	1.17	1.20	0.03	1.33	1.31	-0.03
USA	1.86	1.60	-0.27	1.20	1.20	0.01	1.56	1.33	-0.23

Table 5: Numeracy inequality by country

	P90/P10			P90/P50			P50/P10		
	Level		Change	Level		Change	Level		Change
Country	IALS94	PIAAC12	PIAAC12 - IALS94	IALS94	PIAAC12	PIAAC12 - IALS94	IALS94	PIAAC12	PIAAC12 - IALS94
Belgium	1.51	1.55	0.04	1.17	1.18	0.01	1.29	1.32	0.03
Canada	1.62	1.71	0.09	1.20	1.23	0.02	1.35	1.39	0.05
Chile	2.25	2.07	-0.17	1.30	1.35	0.04	1.73	1.54	-0.19
Czech	1.47	1.46	-0.01	1.16	1.17	0.01	1.27	1.25	-0.02
Denmark	1.37	1.56	0.19	1.13	1.19	0.05	1.21	1.32	0.10
Finland	1.39	1.53	0.14	1.15	1.19	0.04	1.20	1.29	0.08
Germany	1.45	1.56	0.12	1.17	1.18	0.01	1.24	1.32	0.09
Ireland	1.76	1.63	-0.13	1.20	1.22	0.02	1.46	1.34	-0.12
Italy	1.63	1.62	-0.01	1.16	1.23	0.07	1.40	1.32	-0.08
Netherlands	1.41	1.51	0.10	1.14	1.16	0.02	1.23	1.30	0.07
Newzealand	1.54	1.68	0.14	1.18	1.22	0.03	1.30	1.38	0.08
Norway	1.41	1.56	0.16	1.14	1.17	0.03	1.23	1.33	0.10
Poland	2.30	1.60	-0.70	1.25	1.21	-0.04	1.84	1.32	-0.51
Slovenia	2.16	1.66	-0.50	1.24	1.22	-0.02	1.75	1.36	-0.38
Sweden	1.48	1.57	0.10	1.18	1.18	0.00	1.25	1.33	0.08
UK	1.64	1.68	0.03	1.19	1.23	0.04	1.38	1.36	-0.02
USA	2.04	1.72	-0.32	1.23	1.24	0.00	1.65	1.39	-0.26

Table 6: Wage inequality by country in 1994

	CV	P90/P10			P90/P50			P50/P10		
Country		IALS	LOV	OECD	IALS	LOV	OECD	IALS	LOV	OECD
Canada			4.58	3.77		1.75	1.73		2.61	2.18
Chile	0.82	4.44	5.2		2.63	2.57		1.69	2.03	
Czech	0.57	2.29	2.72	2.74	1.6	1.62	1.54	1.43	1.68	1.78
Denmark	0.12	2.34	2.37	2.17	1.59	1.58	1.57	1.47	1.5	1.38
Finland	0.08	2.37	2.56	2.53	1.46	1.43	1.73	1.63	1.79	1.46
Germany			2.78	2.25		1.58	1.64		1.76	1.37
Hungary	1.11	5.64	5.38		2.75	2.62		2.05	2.05	
Italy	0.22	3.2	3.53	2.64	1.92	1.91	1.6	1.67	1.85	1.65
Netherlands			3.05	2.59		1.68	1.66		1.81	1.56
Norway	0.12	2.35	2.79	1.98	1.5	1.52	1.5	1.57	1.83	1.32
Slovenia	0.4	3.50	3.17		1.80	1.9		1.94	1.67	
Sweden			2.75	2.2		1.65	1.62		1.67	1.36
Switzerland	0.18	2.97	2.78	2.44	1.61	1.65	1.64	1.91	1.68	1.49
USA			4.88	4.28		2.01	2.13		2.43	2.01

Note: ”IALS” column uses IALS dataset available to the author. ”LOV” column presents values calculated using ones from Leuven et al. (2004) which uses IALS data. ”OECD” column shows values from OECD (1996) which calculates earnings (not wage) inequalty using each country’s administrative data.

Table 7: Wage inequality by country in 2012

Country	CV	P90/P10			P90/P50			P50/P10		
		PIAAC	BQV	OECD	PIAAC	BQV	OECD	PIAAC	BQV	OECD
Austria			3.06	3.50		1.83	1.80		1.67	2.00
Belgium	0.13	2.60	2.60	3.40	1.69	1.67	1.70	1.54	1.56	2.00
Canada			3.94	4.30		1.94	1.90		2.03	2.20
Chile	0.09	6.56		7.40	3.20		2.90	2.05		2.50
Cyprus	0.21	3.76			2.06			1.83		
Czech	0.13	3.09	2.87	3.00	1.78	1.68	1.80	1.73	1.71	1.70
Denmark	0.11	2.75	2.57	2.80	1.64	1.55	1.60	1.67	1.66	1.70
Estonia	0.35	4.88	4.70	5.20	2.28	2.24	2.20	2.15	2.10	2.30
Finland	0.13	2.62	2.55	3.10	1.68	1.70	1.70	1.56	1.50	1.80
France	0.18	2.60	2.57	3.60	1.79	1.77	1.90	1.46	1.45	1.90
Germany			4.23	3.50		1.88	1.90		2.25	1.90
Greece	0.26	3.72		4.90	2.15		1.90	1.73		2.50
Ireland	0.27	3.68	3.56	3.90	2.04	2.08	2.00	1.80	1.71	1.90
Israel	0.23	4.62		6.10	2.74		2.20	1.69		2.70
Italy	0.2	3.60	3.42	4.40	2.08	1.99	1.90	1.73	1.72	2.30
Japan	0.1	4.37	4.08	5.10	2.20	2.32	2.00	1.99	1.76	2.60
Korea	0.07	6.11	5.84	4.80	2.47	2.68	1.90	2.47	2.18	2.50
Netherlands		3.68	3.24	3.20	1.82	1.79	1.80	2.02	1.81	1.80
Norway	0.09	2.67	2.43	3.00	1.65	1.60	1.60	1.62	1.52	1.90
Poland	0.2	3.61	3.89	3.90	2.12	2.15	1.90	1.70	1.81	2.00
Russia	0.23	5.55			2.24			2.47		
Slovakia	0.43	3.86	4.02	3.20	2.08	2.15	1.70	1.85	1.87	1.90
Slovenia	0.21	2.88		3.20	1.83		1.70	1.57		2.00
Spain	0.23	3.69	3.59	4.90	2.06	2.05	2.00	1.79	1.75	2.40
Sweden			2.18	3.20		1.59	1.70		1.37	1.90
UK	0.23	3.75	3.54	4.20	2.03	2.07	2.10	1.85	1.71	2.00
USA			4.82	6.40		2.40	2.30		2.01	2.70

Note: "PIAAC" column uses wage data in PIAAC available to the author. "BQV" column presents values calculated using ones from Broecke et al. (2018) which also uses PIAAC data. "OECD" column shows income inequality values from OECD Income Distribution Database.

Table 8: Change in wage inequality

Country	△ CV	△ P90/P10			△ P90/P50			△ P50/P10		
		PIAAC	LOV	OECD	PIAAC	LOV	OECD	PIAAC	LOV	OECD
Chile	-0.73	2.11	1.36		0.57	0.63		0.36	0.02	
Czech	-0.44	0.79	0.37	0.26	0.18	0.17	0.26	0.30	0.05	-0.08
Denmark	-0.02	0.38	0.38	0.63	0.05	0.07	0.03	0.18	0.17	0.32
Finland	0.05	0.25	0.06	0.57	0.23	0.25	-0.03	-0.07	-0.23	0.34
Italy	-0.02	0.4	0.08	1.76	0.16	0.17	0.30	0.06	-0.12	0.65
Norway	-0.04	0.29	-0.11	1.02	0.15	0.12	0.10	0.03	-0.21	0.58
Slovenia	-0.19	-0.12	-0.29		0.03	-0.07		-0.09	-0.09	
USA			-0.06	2.12		0.39	0.17		-0.42	0.69

Note: "PIAAC" column uses IALS and PIAAC wage data available to the author. "LOV" column presents values calculated using PIAAC for 2012 and Leuven et al. (2004) for 1994. "OECD" column uses "OECD" column from previous two tables.

Table 9: Comaprison of coefficients between 1994 and 2012

	Complete model						Modified Mincer equation				Mincer equation			
	Literacy		Years of education		Experience		Literacy		Experience		Years of education		Experience	
Country	1994	2012	1994	2012	1994	2012	1994	2012	1994	2012	1994	2012	1994	2012
Belgium		0.531***		0.04***		0.023***		0.832***		0.024***		0.059***		0.024***
Chile	0.459***	0.169	0.077***	0.098***	0.006	0.013**	1.262***	0.845***	0.009	0.007	0.093***	0.105***	0.003	0.013**
Czech	0.181*	0.254**	0.03***	0.055***	0.018***	0.008	0.400***	0.643***	0.01*	0.007	0.032***	0.061***	0.019***	0.008*
Denmark	0.232***	0.397***	0.035***	0.044***	0.035***	0.02***	0.595***	0.630***	0.038***	0.02***	0.04***	0.056***	0.035***	0.02***
Finland	0.453***	0.319***	0.016***	0.051***	0.02***	0.019***	0.608***	0.672***	0.019***	0.023***	0.024***	0.058***	0.019***	0.019***
France		0.301***		0.039***		0.02***		0.654***		0.02***		0.048***		0.02***
Ireland		0.767***		0.045***		0.024***		0.105***		0.022***		0.069***		0.024***
Italy	0.243***	0.434**	0.052***	0.054***	0.049***	0.034***	0.654***	0.636***	0.046***	0.028***	0.06***	0.061***	0.051***	0.035***
Japan		0.203***		0.05***		0.05***		0.636***		0.051***		0.066***		0.053***
Korea		0.580***		0.079***		0.032***		1.147***		0.033***		0.093***		0.03***
Netherlands		0.836***		0.061***		0.023***		1.276***		0.024***		0.087***		0.024***
Norway	0.251***	0.476***	0.027***	0.046***	0.018***	0.018***	0.494***	0.693***	0.006***	0.019***	0.031***	0.059***	0.019***	0.019***
Poland		0.523***		0.069***		0.025***		1.035***		0.023***		0.086***		0.023***
Slovenia	0.265***	0.430***	0.05***	0.09***	0.015**	0.014***	0.611***	0.798***	0.014*	0.008**	0.063***	0.113***	0.016**	0.014***
Spain		0.361***		0.065***		0.008*		0.184***		0.004		0.868***		0.008*
UK		0.965***		0.056***		0.033***		0.226***		0.125***		0.084***		0.036***

Note: Selected for major countries. Each entry is a coefficient of each variable in a OLS regression of three different specifications in two different period. Explained variable is log of hourly wages. Literacy is taken log here, so each entry expresses elasticity (i.e. % change in hourly wage in response to 1% change in literacy). Statistical significance at: ***1%, **5%, *10%.

Table 10: Results of decomposition (Mincer model)

				Price Effects				Composition Effects			
	Inequality measures	Actual	Simulated actual	Total	Constant	Education	Experience	Total	Education	Experience	Residual
Czech	△ P90/P10	0.812	0.33 (0.1)	0.38 (0.06)	1.08 (0.08)	-0.25 (0.05)	0.11 (0.05)	-0.05 (0.12)	-0.04 (0.12)	0.15 (0.06)	0.48 (0.1)
	△ P90/P50	0.202	0.05 (0.05)	0.08 (0.03)	-0.03 (0.02)	-0.03 (0.04)	0.08 (0.04)	-0.03 (0.06)	-0.02 (0.05)	0.07 (0.03)	0.15 (0.05)
	△ P50/P10	0.293	0.17 (0.04)	0.16 (0.03)	0.72 (0.04)	-0.13 (0.03)	-0.01 (0.02)	0 (0.06)	-0.01 (0.06)	0.03 (0.03)	0.12 (0.04)
	△ CV	-0.434	-0.49 (0.03)	-0.48 (0.03)	-0.46 (0.03)	-0.18 (0.02)	0.17 (0.03)	-0.01 (0.01)	-0.01 (0.01)	0.01 (0)	0.06 (0.03)
Denmark	△ P90/P10	0.458	-0.02 (0.08)	0.06 (0.06)	-0.45 (0.05)	0.42 (0.05)	0.58 (0.06)	-0.08 (0.08)	-0.13 (0.08)	0.15 (0.05)	0.48 (0.08)
	△ P90/P50	0.104	0.05 (0.05)	0.08 (0.03)	-0.15 (0.03)	0.17 (0.03)	0.07 (0.02)	-0.03 (0.06)	-0.05 (0.06)	0.1 (0.03)	0.05 (0.05)
	△ P90/P10	0.185	-0.06 (0.04)	-0.04 (0.03)	-0.17 (0.03)	0.09 (0.03)	0.31 (0.04)	-0.02 (0.03)	-0.04 (0.04)	0.01 (0.03)	0.25 (0.04)
	△ CV	-0.014	-0.05 (0)	-0.05 (0)	-0.06 (0)	0.01 (0)	0.03 (0)	0 (0)	0 (0)	0.01 (0)	0.04 (0)
Finland	△ P90/P10	0.252	0.15 (0.09)	0.12 (0.07)	-0.6 (0.05)	0.25 (0.06)	0.62 (0.05)	0.03 (0.08)	-0.17 (0.09)	0.35 (0.04)	0.1 (0.09)
	△ P90/P50	0.226	0.17 (0.04)	0.16 (0.03)	-0.19 (0.02)	0.13 (0.03)	0.27 (0.02)	0 (0.05)	-0.06 (0.05)	0.17 (0.03)	0.06 (0.04)
	△ P90/P10	-0.069	-0.08 (0.05)	-0.09 (0.04)	-0.24 (0.03)	0.03 (0.04)	0.11 (0.03)	0.02 (0.05)	-0.05 (0.05)	0.07 (0.02)	-0.62 (0.05)
	△ CV	0.049	0.04 (0.003)	0.04 (0.002)	0.01 (0.001)	0.01 (0.001)	0.02 (0)	0 (0.003)	-0.01 (0.003)	0.02 (0.001)	0.01 (0.003)
Italy	△ P90/P10	0.534	-0.04 (0.16)	0.08 (0.1)	-0.25 (0.1)	-0.24 (0.09)	0.66 (0.17)	-0.11 (0.15)	-0.4 (0.16)	0.5 (0.07)	0.57 (0.16)
	△ P90/P50	0.240	0.07 (0.09)	0.11 (0.03)	0.13 (0.04)	-0.13 (0.04)	-0.02 (0.05)	-0.04 (0.09)	-0.14 (0.09)	0.1 (0.04)	0.17 (0.09)
	△ P90/P10	0.064	-0.09 (0.07)	-0.06 (0.05)	-0.25 (0.06)	-0.01 (0.03)	0.4 (0.08)	-0.03 (0.05)	-0.09 (0.07)	0.18 (0.04)	0.15 (0.07)
	△ CV	-0.015	-0.03 (0.006)	0.08 (0.098)	-0.25 (0.1)	-0.24 (0.085)	0.66 (0.167)	-0.11 (0.155)	-0.4 (0.163)	0.5 (0.074)	0.02 (0.006)
Norway	△ P90/P10	0.349	0.11 (0.08)	0.24 (0.06)	-0.58 (0.04)	0.65 (0.07)	0.44 (0.06)	-0.13 (0.1)	-0.18 (0.12)	0.23 (0.04)	0.24 (0.08)
	△ P90/P50	0.186	0.11 (0.04)	0.18 (0.04)	-0.15 (0.02)	0.21 (0.04)	0.07 (0.02)	-0.07 (0.06)	-0.08 (0.06)	0.08 (0.02)	0.08 (0.04)
	△ P90/P10	0.032	-0.04 (0.04)	-0.02 (0.03)	-0.28 (0.03)	0.2 (0.03)	0.22 (0.03)	-0.02 (0.04)	-0.04 (0.05)	0.08 (0.02)	0.07 (0.04)
	△CV	-0.033	-0.05 (0.003)	-0.04 (0.003)	-0.06 (0.002)	0.02 (0.005)	0.02 (0.002)	-0.01 (0.004)	-0.03 (0.013)	0.01 (0.001)	0.02 (0.003)
Slovenia	△ P90/P10	-0.04	-0.19 (0.12)	0.4 (0.11)	-0.33 (0.07)	1.18 (0.15)	0.47 (0.07)	-0.58 (0.14)	-0.61 (0.15)	0.25 (0.06)	0.15 (0.12)
	△ P90/P50	0.017	0.01 (0.07)	0.18 (0.04)	0.19 (0.04)	0.05 (0.06)	-0.09 (0.04)	-0.17 (0.08)	-0.18 (0.08)	-0.04 (0.03)	0.01 (0.07)
	△ P90/P10	-0.057	-0.12 (0.05)	0.05 (0.05)	-0.35 (0.04)	0.63 (0.07)	0.39 (0.04)	-0.17 (0.06)	-0.17 (0.06)	0.18 (0.03)	0.06 (0.05)
	△ CV	-0.184	-0.17 (0.009)	-0.14 (0.005)	-0.13 (0.004)	-0.04 (0.004)	0.07 (0.004)	-0.03 (0.008)	-0.03 (0.008)	0.01 (0.002)	-0.01 (0.009)

Note: Decomposition results using Mincer model, by country and by inequality measures. First two columns are actual change in inequality and simulated change in inequality. Next four columns represent total price effect and individual price effect, followed by total composition effect and individual composition effect. Last column shows the residual, that is the difference between actual and simulated actual change in inequalities. Each entry shows a mean value of 50 simulations, with standard deviation in bracket.

Table 11: Results of decomposition (Complete model)

				Price Effects					Composition Effects				
	Inequality measures	Actual	Simulated actual	Total	Constant	Literacy	Education	Experience	Total	Literacy	Education	Experience	Residual
Czech	△ P90/P10	0.81	0.3 (0.06)	0.35 (0.06)	0.69 (0.08)	-0.19 (0.05)	-0.2 (0.05)	0.05 (0.04)	-0.05 (0.05)	0.01 (0.02)	-0.05 (0.05)	-0.03 (0.04)	0.51 (0.06)
	△ P90/P50	0.20	0.03 (0.03)	0.06 (0.03)	-0.01 (0.07)	-0.03 (0.04)	0.01 (0.04)	0.1 (0.03)	-0.03 (0.03)	0 (0.01)	-0.02 (0.02)	-0.02 (0.02)	0.17 (0.03)
	△ P50/P10	0.29	0.16 (0.02)	0.16 (0.03)	0.45 (0.05)	-0.1 (0.02)	-0.13 (0.02)	-0.06 (0.02)	0 (0.03)	0 (0.01)	-0.01 (0.02)	0 (0.01)	0.13 (0.02)
	△ CV	-0.43	-0.51 (0.058)	-0.5 (0.049)	-0.35 (0.048)	-0.15 (0.013)	-0.15 (0.045)	0.16 (0.016)	-0.01 (0.011)	0 (0)	-0.01 (0.011)	0 (0)	0.08 (0.058)
Denmark	△ P90/P10	0.46	-0.01 (0.05)	0.02 (0.06)	-0.92 (0.08)	0.24 (0.05)	0.18 (0.04)	0.51 (0.06)	-0.03 (0.06)	0.03 (0.02)	-0.09 (0.04)	0.02 (0.02)	0.47 (0.05)
	△ P90/P50	0.10	0.04 (0.02)	0.06 (0.03)	-0.12 (0.04)	0.07 (0.03)	0.08 (0.02)	0.04 (0.02)	-0.03 (0.03)	0 (0.01)	-0.04 (0.02)	0.01 (0.02)	0.06 (0.02)
	△ P90/P10	0.19	-0.04 (0.03)	-0.05 (0.03)	-0.48 (0.05)	0.09 (0.03)	0.05 (0.02)	0.29 (0.03)	0 (0.03)	0.02 (0.01)	-0.02 (0.02)	0 (0.01)	0.23 (0.03)
	△ CV	-0.01	-0.05 (0.002)	-0.05 (0.001)	-0.09 (0.001)	0.01 (0.001)	0.01 (0.001)	0.03 (0.001)	0 (0.001)	0 (0)	0 (0.001)	0 (0)	0.04 (0.002)
Finland	△ P90/P10	0.25	0.06 (0.06)	0.13 (0.07)	-1.83 (0.1)	1.32 (0.07)	0.14 (0.07)	0.51 (0.05)	-0.06 (0.05)	0.01 (0.02)	-0.08 (0.05)	0.02 (0.03)	0.19 (0.06)
	△ P90/P50	0.23	0.15 (0.03)	0.18 (0.03)	-0.55 (0.04)	0.38 (0.03)	0.12 (0.03)	0.23 (0.02)	-0.03 (0.03)	0.01 (0.01)	-0.04 (0.03)	0 (0.02)	0.08 (0.03)
	△ P90/P10	-0.07	-0.12 (0.04)	-0.11 (0.04)	-0.53 (0.06)	0.39 (0.04)	-0.05 (0.04)	0.07 (0.03)	-0.01 (0.02)	0 (0.01)	-0.02 (0.02)	0.01 (0.02)	-0.58 (0.04)
	△ CV	0.05	0.04 (0.002)	0.04 (0.002)	-0.02 (0.001)	0.04 (0)	0 (0.001)	0.02 (0)	0 (0.001)	0 (0)	-0.01 (0.001)	0 (0)	0.01 (0.002)
Italy	△ P90/P10	0.53	0.05 (0.11)	0.12 (0.08)	-0.17 (0.23)	-0.83 (0.11)	0.43 (0.11)	0.7 (0.13)	-0.07 (0.1)	0 (0.04)	-0.12 (0.09)	0.03 (0.05)	0.48 (0.11)
	△ P90/P50	0.24	0.11 (0.05)	0.12 (0.04)	0.37 (0.09)	-0.24 (0.05)	0 (0.04)	-0.01 (0.04)	-0.01 (0.05)	0 (0.01)	-0.03 (0.05)	0.01 (0.02)	0.13 (0.05)
	△ P90/P10	0.06	-0.07 (0.04)	-0.05 (0.04)	-0.43 (0.1)	-0.27 (0.06)	0.24 (0.05)	0.41 (0.06)	-0.03 (0.03)	0 (0.02)	-0.03 (0.03)	0 (0.02)	0.14 (0.04)
	△ CV	-0.02	-0.03 (0.004)	-0.03 (0.003)	-0.06 (0.005)	-0.05 (0.005)	0.04 (0.002)	0.05 (0.002)	0 (0.003)	0 (0.001)	0 (0.002)	0 (0.001)	0.02 (0.004)
Norway	△ P90/P10	0.35	0.08 (0.06)	0.21 (0.06)	-0.59 (0.09)	0.06 (0.05)	0.4 (0.06)	0.34 (0.05)	-0.13 (0.06)	0.02 (0.02)	-0.11 (0.05)	-0.04 (0.04)	0.27 (0.06)
	△ P90/P50	0.19	0.09 (0.03)	0.15 (0.03)	-0.13 (0.05)	0.05 (0.03)	0.17 (0.03)	0.06 (0.02)	-0.05 (0.03)	0 (0.01)	-0.04 (0.03)	-0.02 (0.02)	0.09 (0.03)
	△ P90/P10	0.03	-0.04 (0.03)	-0.01 (0.03)	-0.25 (0.05)	-0.01 (0.03)	0.09 (0.03)	0.16 (0.03)	-0.03 (0.03)	0.01 (0.01)	-0.03 (0.02)	-0.01 (0.02)	0.08 (0.03)
	△ CV	-0.03	-0.07 (0.016)	-0.05 (0.004)	-0.09 (0.005)	0.01 (0.003)	0.02 (0.007)	0.02 (0.002)	-0.02 (0.013)	0 (0)	-0.02 (0.009)	-0.01 (0.006)	0.04 (0.016)
Slovenia	△ P90/P10	-0.04	-0.14 (0.07)	0.22 (0.08)	-1.42 (0.14)	1.04 (0.1)	0.35 (0.11)	0.26 (0.08)	-0.37 (0.11)	0 (0.03)	-0.34 (0.1)	-0.02 (0.03)	0.1 (0.07)
	△ P90/P50	0.02	0.02 (0.04)	0.15 (0.05)	0.03 (0.07)	0.23 (0.04)	0.01 (0.06)	-0.12 (0.04)	-0.12 (0.05)	-0.01 (0.01)	-0.1 (0.05)	-0.01 (0.02)	-0.01 (0.04)
	△ P90/P10	-0.06	-0.11 (0.04)	-0.01 (0.04)	-0.84 (0.08)	0.35 (0.05)	0.19 (0.04)	0.29 (0.04)	-0.1 (0.04)	0.01 (0.01)	-0.1 (0.04)	0 (0.01)	0.05 (0.04)
	△ CV	-0.18	-0.17 (0.005)	-0.15 (0.004)	-0.19 (0.003)	0.04 (0.003)	-0.05 (0.004)	0.04 (0.002)	-0.02 (0.005)	0 (0.001)	-0.02 (0.004)	0 (0)	-0.01 (0.005)

Note: Complete model version of the previous table.

Table 12: Result of marginal effect analysis (Mincer model)

				Price Effects				Composition Effects		
	Inequality measures	Actual	Simulated actual	Total	Constant	Education	Experience	Total	Education	Experience
Czech	P90/P10 in 2012	3.09	2.57 (0.09)	-0.32 (0.08)	-0.46 (0.08)	0.92 (0.11)	-0.15 (0.06)	0.05 (0.12)	0.04 (0.12)	-0.15 (0.06)
	P90/P50 in 2012	1.78	1.61 (0.04)	-0.06 (0.04)	-0.04 (0.03)	-0.07 (0.04)	-0.07 (0.03)	0.03 (0.06)	0.02 (0.05)	-0.07 (0.03)
	P50/P10 in 2012	1.73	1.6 (0.04)	-0.14 (0.03)	-0.25 (0.04)	0.66 (0.06)	-0.03 (0.03)	0 (0.06)	0.01 (0.06)	-0.03 (0.03)
	CV in 2012	0.13	0.08 (0.002)	0.48 (0.009)	0.34 (0.008)	0.03 (0.001)	-0.01 (0.001)	0.01 (0.009)	0.01 (0.012)	-0.01 (0.001)
Denmark	P90/P10 in 2012	2.75	2.2 (0.06)	0.06 (0.05)	1 (0.08)	-0.39 (0.04)	-0.15 (0.05)	0.08 (0.08)	0.13 (0.08)	-0.15 (0.05)
	P90/P50 in 2012	1.64	1.54 (0.04)	-0.06 (0.03)	0.18 (0.04)	-0.19 (0.03)	-0.1 (0.03)	0.03 (0.06)	0.05 (0.06)	-0.1 (0.03)
	P50/P10 in 2012	1.67	1.43 (0.02)	0.1 (0.04)	0.43 (0.04)	-0.09 (0.02)	-0.01 (0.03)	0.02 (0.03)	0.04 (0.04)	-0.01 (0.03)
	CV in 2012	0.11	0.06 (0.001)	0.06 (0.002)	0.09 (0.001)	0 (0.001)	-0.01 (0.001)	0 (0.002)	0 (0.002)	-0.01 (0.001)
Finland	P90/P10 in 2012	2.62	2.43 (0.06)	0.02 (0.06)	0.86 (0.08)	-0.33 (0.05)	-0.35 (0.04)	-0.03 (0.08)	0.17 (0.09)	-0.35 (0.04)
	P90/P50 in 2012	1.68	1.57 (0.04)	-0.13 (0.03)	0.22 (0.03)	-0.14 (0.03)	-0.17 (0.03)	0 (0.05)	0.06 (0.05)	-0.17 (0.03)
	P50/P10 in 2012	1.56	1.54 (0.04)	0.15 (0.04)	0.29 (0.04)	-0.07 (0.03)	-0.07 (0.02)	-0.02 (0.05)	0.05 (0.05)	-0.07 (0.02)
	CV in 2012	0.13	0.11 (0.003)	-0.03 (0.002)	-0.02 (0.001)	0 (0.001)	-0.02 (0.001)	0 (0.003)	0.01 (0.003)	-0.02 (0.001)
Italy	P90/P10 in 2012	3.6	3.13 (0.1)	-0.09 (0.1)	0.35 (0.11)	0.17 (0.09)	-0.5 (0.07)	0.11 (0.15)	0.4 (0.16)	-0.5 (0.07)
	P90/P50 in 2012	2.08	1.86 (0.06)	-0.12 (0.03)	-0.18 (0.05)	0.16 (0.05)	-0.1 (0.04)	0.04 (0.09)	0.14 (0.09)	-0.1 (0.04)
	P50/P10 in 2012	1.73	1.69 (0.04)	0.06 (0.05)	0.4 (0.06)	-0.05 (0.03)	-0.18 (0.04)	0.03 (0.05)	0.09 (0.07)	-0.18 (0.04)
	CV in 2012	0.2	0.17 (0.003)	0.03 (0.004)	0.1 (0.001)	0.02 (0.001)	-0.02 (0.002)	0 (0.005)	0.02 (0.005)	-0.02 (0.002)
Norway	P90/P10 in 2012	2.67	2.28 (0.06)	-0.08 (0.05)	0.91 (0.06)	-0.56 (0.05)	-0.23 (0.04)	0.13 (0.1)	0.18 (0.12)	-0.23 (0.04)
	P90/P50 in 2012	1.65	1.55 (0.04)	-0.12 (0.02)	0.09 (0.03)	-0.22 (0.03)	-0.08 (0.02)	0.07 (0.06)	0.08 (0.06)	-0.08 (0.02)
	P50/P10 in 2012	1.62	1.47 (0.03)	0.06 (0.03)	0.47 (0.03)	-0.18 (0.03)	-0.08 (0.02)	0.02 (0.04)	0.04 (0.05)	-0.08 (0.02)
	CV in 2012	0.09	0.06 (0.001)	0.05 (0.001)	0.07 (0.001)	0 (0.001)	-0.01 (0.001)	0.01 (0.004)	0.03 (0.013)	-0.01 (0.001)
Slovenia	P90/P10 in 2012	2.88	2.68 (0.07)	0 (0.08)	1.46 (0.13)	-0.4 (0.07)	-0.25 (0.06)	0.58 (0.14)	0.61 (0.15)	-0.25 (0.06)
	P90/P50 in 2012	1.83	1.7 (0.04)	-0.09 (0.04)	-0.17 (0.05)	0.12 (0.04)	0.04 (0.03)	0.17 (0.08)	0.18 (0.08)	0.04 (0.03)
	P50/P10 in 2012	1.58	1.57 (0.03)	0.09 (0.04)	1.12 (0.07)	-0.32 (0.03)	-0.18 (0.03)	0.17 (0.06)	0.17 (0.06)	-0.18 (0.03)
	CV in 2012	0.21	0.19 (0.004)	0.17 (0.005)	0.16 (0.002)	0.04 (0.002)	-0.01 (0.002)	0.03 (0.008)	0.03 (0.008)	-0.01 (0.002)

Note: Results of marginal effect analysis for Mincer model. Each entry reads how much 2012 wage inequality meaures will change if a variable's composition or price is like 1994. Positive values mean that inequality could have been larger.

Table 13: Result of marginal effect analysis (Complete model)

				Price Effects					Composition Effects			
	Inequality measures	Actual	Simulated actual	Total	Constant	Literacy	Education	Experience	Total	Literacy	Education	Experience
Czech	P90/P10 in 2012	3.09	2.54 (0.08)	-0.29 (0.06)	-0.42 (0.08)	0.34 (0.11)	0.95 (0.08)	-0.1 (0.06)	0.05 (0.05)	-0.01 (0.02)	0.05 (0.05)	0.03 (0.04)
	P90/P50 in 2012	1.78	1.59 (0.04)	-0.04 (0.03)	-0.01 (0.05)	0.1 (0.07)	-0.04 (0.04)	-0.09 (0.04)	0.03 (0.03)	0 (0.01)	0.02 (0.02)	0.02 (0.02)
	P50/P10 in 2012	1.73	1.6 (0.03)	-0.14 (0.03)	-0.26 (0.03)	0.11 (0.03)	0.66 (0.04)	0.04 (0.03)	0 (0.03)	0 (0.01)	0.01 (0.02)	0 (0.01)
	CV in 2012	0.13	0.08 (0.002)	0.49 (0.01)	0.29 (0.008)	0.02 (0.001)	0.03 (0.001)	0 (0)	0.01 (0.011)	0 (0)	0.01 (0.011)	0 (0)
Denmark	P90/P10 in 2012	2.75	2.19 (0.05)	0.1 (0.06)	1.09 (0.06)	-0.21 (0.04)	-0.22 (0.04)	-0.15 (0.06)	0.03 (0.04)	-0.04 (0.03)	0.09 (0.04)	-0.01 (0.03)
	P90/P50 in 2012	1.64	1.52 (0.04)	-0.04 (0.03)	0.13 (0.03)	-0.1 (0.03)	-0.1 (0.02)	-0.09 (0.03)	0.02 (0.02)	0 (0.01)	0.03 (0.02)	0 (0.02)
	P50/P10 in 2012	1.67	1.44 (0.03)	0.11 (0.03)	0.55 (0.04)	-0.05 (0.02)	-0.06 (0.02)	-0.02 (0.03)	0 (0.02)	-0.02 (0.01)	0.02 (0.02)	-0.01 (0.01)
	CV in 2012	0.11	0.06 (0.001)	0.06 (0.002)	0.09 (0.001)	0 (0.001)	0 (0.001)	-0.01 (0.001)	0 (0.001)	0 (0)	0 (0.001)	0 (0)
Finland	P90/P10 in 2012	2.62	2.38 (0.05)	0.05 (0.06)	2.11 (0.12)	-0.49 (0.05)	-0.11 (0.05)	-0.28 (0.04)	0.05 (0.05)	-0.01 (0.01)	0.09 (0.05)	-0.02 (0.03)
	P90/P50 in 2012	1.68	1.54 (0.03)	-0.13 (0.03)	0.67 (0.04)	-0.2 (0.04)	-0.13 (0.03)	-0.15 (0.02)	0.03 (0.03)	0 (0.01)	0.04 (0.03)	0 (0.02)
	P50/P10 in 2012	1.56	1.55 (0.03)	0.18 (0.03)	0.48 (0.05)	-0.14 (0.03)	0.06 (0.03)	-0.04 (0.02)	0.01 (0.03)	0 (0.01)	0.02 (0.02)	-0.01 (0.02)
	CV in 2012	0.13	0.11 (0.002)	-0.03 (0.002)	0.02 (0.001)	-0.02 (0.002)	0.02 (0.001)	-0.01 (0.001)	0 (0.002)	0 (0)	0.01 (0.001)	0 (0)
Italy	P90/P10 in 2012	3.6	3.11 (0.1)	-0.06 (0.11)	-0.92 (0.07)	3.92 (0.26)	-0.34 (0.07)	-0.44 (0.09)	0.07 (0.1)	-0.01 (0.04)	0.11 (0.09)	-0.03 (0.04)
	P90/P50 in 2012	2.08	1.86 (0.04)	-0.13 (0.03)	-0.38 (0.04)	0.46 (0.07)	-0.03 (0.04)	-0.11 (0.04)	0.01 (0.04)	-0.01 (0.01)	0.03 (0.04)	-0.01 (0.02)
	P50/P10 in 2012	1.73	1.67 (0.04)	0.09 (0.05)	-0.19 (0.04)	1.36 (0.11)	-0.17 (0.03)	-0.14 (0.05)	0.03 (0.03)	0 (0.02)	0.04 (0.03)	-0.01 (0.02)
	CV in 2012	0.2	0.17 (0.004)	0.03 (0.003)	-0.02 (0.002)	0.14 (0.002)	-0.01 (0.001)	-0.02 (0.001)	0 (0.003)	0 (0.001)	0 (0.002)	0 (0.001)
Norway	P90/P10 in 2012	2.67	2.31 (0.06)	-0.1 (0.05)	0.8 (0.07)	-0.18 (0.05)	-0.42 (0.05)	-0.18 (0.04)	0.13 (0.06)	-0.02 (0.02)	0.11 (0.05)	0.04 (0.04)
	P90/P50 in 2012	1.65	1.55 (0.04)	-0.11 (0.03)	0.17 (0.03)	-0.07 (0.03)	-0.17 (0.03)	-0.07 (0.02)	0.05 (0.03)	0 (0.01)	0.04 (0.03)	0.01 (0.02)
	P50/P10 in 2012	1.62	1.49 (0.03)	0.05 (0.03)	0.31 (0.03)	-0.05 (0.03)	-0.12 (0.02)	-0.05 (0.02)	0.03 (0.03)	-0.01 (0.01)	0.03 (0.02)	0.01 (0.03)
	CV in 2012	0.09	0.06 (0.001)	0.05 (0.001)	0.07 (0.001)	0 (0.001)	0 (0.001)	0 (0)	0.02 (0.014)	0 (0)	0.02 (0.01)	0.01 (0.006)
Slovenia	P90/P10 in 2012	2.88	2.67 (0.06)	-0.03 (0.06)	1.79 (0.11)	-0.67 (0.05)	0 (0.06)	-0.13 (0.05)	0.34 (0.08)	0 (0.03)	0.33 (0.08)	0.01 (0.02)
	P90/P50 in 2012	1.83	1.7 (0.05)	-0.11 (0.04)	-0.05 (0.04)	-0.22 (0.04)	0.21 (0.04)	0.06 (0.04)	0.11 (0.04)	0.01 (0.02)	0.09 (0.04)	0 (0.02)
	P50/P10 in 2012	1.58	1.58 (0.03)	0.08 (0.03)	1.14 (0.07)	-0.22 (0.03)	-0.17 (0.03)	-0.13 (0.03)	0.09 (0.04)	-0.01 (0.02)	0.1 (0.03)	0.01 (0.01)
	CV in 2012	0.21	0.19 (0.003)	0.16 (0.004)	0.15 (0.002)	0 (0.002)	0.05 (0.002)	-0.01 (0.001)	0.02 (0.005)	0 (0.001)	0.02 (0.004)	0 (0)

Note: Complete model version of the previous table.

Table 14: Results of decomposition for Mincer model (reverse order)

				Price Effects				Composition Effects			
	Inequality measures	Actual	Simulated actual	Total	Constant	Education	Experience	Total	Education	Experience	Residual
Czech	△ P90/P10	0.81	0.33 (0.1)	0.32 (0.08)	0.46 (0.08)	-0.92 (0.11)	0.15 (0.06)	0.01 (0.07)	-0.02 (0.07)	0.11 (0.05)	0.48 (0.1)
	△ P90/P50	0.2	0.05 (0.05)	0.06 (0.04)	0.04 (0.03)	0.07 (0.04)	0.07 (0.03)	-0.02 (0.05)	-0.01 (0.05)	0.08 (0.04)	0.15 (0.05)
	△ P90/P10	0.29	0.17 (0.04)	0.14 (0.03)	0.25 (0.04)	-0.66 (0.06)	0.03 (0.03)	0.02 (0.03)	-0.01 (0.03)	-0.01 (0.02)	0.12 (0.04)
	△ CV	-0.43	-0.49 (0.03)	-0.48 (0.01)	-0.34 (0.01)	-0.03 (0)	0.01 (0)	0 (0.04)	-0.01 (0.05)	0.17 (0.03)	0.06 (0.03)
Denmark	△ P90/P10	0.46	-0.02 (0.08)	-0.06 (0.05)	-1 (0.08)	0.39 (0.04)	0.15 (0.05)	0.04 (0.09)	0 (0.07)	0.58 (0.06)	0.48 (0.08)
	△ P90/P50	0.1	0.05 (0.05)	0.06 (0.03)	-0.18 (0.04)	0.19 (0.03)	0.1 (0.03)	-0.01 (0.05)	-0.01 (0.05)	0.07 (0.02)	0.05 (0.05)
	△ P90/P10	0.19	-0.06 (0.04)	-0.1 (0.04)	-0.43 (0.04)	0.09 (0.02)	0.01 (0.03)	0.04 (0.06)	0 (0.04)	0.31 (0.04)	0.25 (0.04)
	△ CV	-0.01	-0.05 (0)	-0.06 (0)	-0.09 (0)	0 (0)	0.01 (0)	0.01 (0)	0 (0)	0.03 (0)	0.04 (0)
Finland	△ P90/P10	0.25	0.15 (0.09)	-0.02 (0.06)	-0.86 (0.08)	0.33 (0.05)	0.35 (0.04)	0.17 (0.09)	0.05 (0.05)	0.62 (0.05)	0.1 (0.09)
	△ P90/P50	0.23	0.17 (0.04)	0.13 (0.03)	-0.22 (0.03)	0.14 (0.03)	0.17 (0.03)	0.04 (0.03)	0.02 (0.02)	0.27 (0.02)	0.06 (0.04)
	△ P90/P10	-0.07	-0.08 (0.05)	-0.15 (0.04)	-0.29 (0.04)	0.07 (0.03)	0.07 (0.02)	0.07 (0.06)	0.02 (0.04)	0.11 (0.03)	-0.62 (0.05)
	△ CV	0.05	0.04 (0.003)	0.03 (0.002)	0.02 (0.001)	0 (0.001)	0.02 (0.001)	0.01 (0.002)	0 (0.001)	0.02 (0)	0.01 (0.003)
Italy	△ P90/P10	0.530	-0.04 (0.16)	0.09 (0.1)	-0.35 (0.11)	-0.17 (0.09)	0.5 (0.07)	-0.12 (0.2)	0.06 (0.18)	0.66 (0.17)	0.57 (0.16)
	△ P90/P50	0.240	0.07 (0.09)	0.12 (0.03)	0.18 (0.05)	-0.16 (0.05)	0.1 (0.04)	-0.04 (0.08)	0.03 (0.09)	-0.02 (0.05)	0.17 (0.09)
	△ P90/P10	0.060	-0.09 (0.07)	-0.06 (0.05)	-0.4 (0.06)	0.05 (0.03)	0.18 (0.04)	-0.03 (0.09)	0 (0.07)	0.4 (0.08)	0.15 (0.07)
	△ CV	-0.020	-0.03 (0.006)	0.09 (0.099)	-0.35 (0.105)	-0.17 (0.088)	0.5 (0.074)	-0.12 (0.202)	0.06 (0.178)	0.66 (0.167)	0.02 (0.006)
Norway	△ P90/P10	0.35	0.11 (0.08)	0.08 (0.05)	-0.91 (0.06)	0.56 (0.05)	0.23 (0.04)	0.03 (0.07)	-0.03 (0.06)	0.44 (0.06)	0.24 (0.08)
	△ P90/P50	0.19	0.11 (0.04)	0.12 (0.02)	-0.09 (0.03)	0.22 (0.03)	0.08 (0.02)	-0.01 (0.03)	-0.02 (0.03)	0.07 (0.02)	0.08 (0.04)
	△ P90/P10	0.03	-0.04 (0.04)	-0.06 (0.03)	-0.47 (0.03)	0.18 (0.03)	0.08 (0.02)	0.03 (0.05)	0 (0.03)	0.22 (0.03)	0.07 (0.04)
	△ CV	-0.03	-0.05 (0.003)	-0.05 (0.001)	-0.07 (0.001)	0 (0.001)	0.01 (0.001)	0 (0.003)	0.02 (0.014)	0.02 (0.002)	0.02 (0.003)
Slovenia	△ P90/P10	-0.04	-0.19 (0.12)	0 (0.08)	-1.46 (0.13)	0.4 (0.07)	0.25 (0.06)	-0.19 (0.1)	-0.13 (0.11)	0.47 (0.07)	0.15 (0.12)
	△ P90/P50	0.02	0.01 (0.07)	0.09 (0.04)	0.17 (0.05)	-0.12 (0.04)	-0.04 (0.03)	-0.09 (0.06)	-0.04 (0.05)	-0.09 (0.04)	0.01 (0.07)
	△ P90/P10	-0.06	-0.12 (0.05)	-0.09 (0.04)	-1.12 (0.07)	0.32 (0.03)	0.18 (0.03)	-0.03 (0.06)	-0.03 (0.05)	0.39 (0.04)	0.06 (0.05)
	△ CV	-0.18	-0.17 (0.009)	-0.17 (0.005)	-0.16 (0.002)	-0.04 (0.002)	0.01 (0.002)	0 (0.009)	0 (0.008)	0.07 (0.004)	-0.01 (0.009)

Note: Decomposition result for Mincer model in reverse order specified in equation (8). This corresponding to Table 10.

Table 15: Results of decomposition for Complete model (reverse order)

				Price Effects					Composition Effects				
	Inequality measures	Actual	Simulated actual	Total	Constant	Literacy	Education	Experience	Total	Literacy	Education	Experience	Residual
Czech	△ P90/P10	0.81	0.3 (0.06)	0.29 (0.06)	1.48 (0.12)	-0.34 (0.11)	-0.95 (0.08)	0.1 (0.06)	0.01 (0.04)	0 (0.01)	-0.02 (0.03)	0.03 (0.02)	0.51 (0.06)
	△ P90/P50	0.20	0.03 (0.03)	0.04 (0.03)	0 (0.07)	-0.1 (0.07)	0.04 (0.04)	0.09 (0.04)	-0.01 (0.02)	0 (0.01)	-0.01 (0.02)	0 (0.01)	0.17 (0.03)
	△ P90/P10	0.29	0.16 (0.02)	0.14 (0.03)	0.95 (0.05)	-0.11 (0.03)	-0.66 (0.04)	-0.04 (0.03)	0.02 (0.02)	0 (0)	0 (0.01)	0.02 (0.02)	0.13 (0.02)
	△ CV	-0.43	-0.51 (0.058)	-0.49 (0.01)	-0.44 (0.01)	-0.02 (0.001)	-0.03 (0.001)	0 (0)	-0.03 (0.057)	0 (0.002)	-0.06 (0.045)	0.03 (0.017)	0.08 (0.058)
Denmark	△ P90/P10	0.46	-0.01 (0.05)	-0.1 (0.06)	-0.69 (0.06)	0.22 (0.04)	0.22 (0.03)	0.15 (0.04)	0.09 (0.06)	0.03 (0.02)	-0.04 (0.04)	0.11 (0.05)	0.47 (0.05)
	△ P90/P50	0.10	0.04 (0.02)	0.04 (0.02)	-0.24 (0.04)	0.1 (0.03)	0.1 (0.03)	0.08 (0.02)	0 (0.02)	0 (0.01)	-0.01 (0.02)	0.02 (0.01)	0.06 (0.02)
	△ P90/P10	0.19	-0.04 (0.03)	-0.1 (0.03)	-0.24 (0.05)	0.06 (0.03)	0.06 (0.02)	0.02 (0.02)	0.06 (0.04)	0.02 (0.01)	-0.01 (0.02)	0.05 (0.03)	0.23 (0.03)
	△ CV	-0.01	-0.05 (0.002)	-0.06 (0.001)	-0.06 (0.002)	0 (0.001)	0 (0.001)	0.01 (0.001)	0.01 (0.002)	0 (0)	0 (0.001)	0.01 (0.002)	0.04 (0.002)
Finland	△ P90/P10	0.25	0.06 (0.06)	-0.05 (0.06)	-0.95 (0.13)	0.5 (0.07)	0.12 (0.06)	0.28 (0.05)	0.12 (0.04)	0 (0.02)	-0.01 (0.02)	0.13 (0.05)	0.19 (0.06)
	△ P90/P50	0.23	0.15 (0.03)	0.13 (0.03)	-0.36 (0.06)	0.2 (0.04)	0.13 (0.04)	0.15 (0.03)	0.02 (0.01)	0 (0.01)	-0.01 (0.01)	0.03 (0.01)	0.08 (0.03)
	△ P90/P10	-0.07	-0.12 (0.04)	-0.18 (0.03)	-0.29 (0.06)	0.14 (0.03)	-0.06 (0.03)	0.03 (0.02)	0.06 (0.03)	0 (0.01)	0 (0.01)	0.05 (0.03)	-0.58 (0.04)
	△ CV	0.05	0.04 (0.002)	0.03 (0.002)	0.01 (0.002)	0.02 (0.002)	-0.02 (0.001)	0.01 (0.001)	0 (0.001)	0 (0)	0 (0)	0 (0.001)	0.01 (0.002)
Italy	△ P90/P10	0.53	0.05 (0.11)	0.06 (0.08)	3.22 (0.35)	-3.91 (0.32)	0.32 (0.08)	0.43 (0.08)	-0.01 (0.09)	-0.02 (0.02)	-0.08 (0.06)	0.07 (0.06)	0.48 (0.11)
	△ P90/P50	0.24	0.11 (0.05)	0.13 (0.04)	0.48 (0.07)	-0.47 (0.07)	0.02 (0.03)	0.1 (0.03)	-0.02 (0.03)	0 (0.01)	-0.03 (0.03)	0.01 (0.02)	0.13 (0.05)
	△ P90/P10	0.06	-0.07 (0.04)	-0.09 (0.05)	0.95 (0.15)	-1.34 (0.13)	0.16 (0.04)	0.15 (0.05)	0.02 (0.04)	-0.01 (0.01)	-0.01 (0.03)	0.03 (0.03)	0.14 (0.04)
	△ CV	-0.02	-0.03 (0.004)	-0.03 (0.003)	0.08 (0.002)	-0.14 (0.002)	0.01 (0.001)	0.02 (0.001)	0 (0.004)	0 (0.001)	0 (0.002)	0 (0.002)	0.02 (0.004)
Norway	△ P90/P10	0.35	0.08 (0.06)	0.08 (0.06)	-0.64 (0.08)	0.17 (0.05)	0.39 (0.05)	0.16 (0.04)	-0.01 (0.05)	0.01 (0.02)	-0.07 (0.04)	0.04 (0.04)	0.27 (0.06)
	△ P90/P50	0.19	0.09 (0.03)	0.11 (0.03)	-0.18 (0.05)	0.07 (0.03)	0.16 (0.03)	0.06 (0.02)	-0.01 (0.02)	0 (0.01)	-0.02 (0.02)	0 (0.01)	0.09 (0.03)
	△ P90/P10	0.03	-0.04 (0.03)	-0.05 (0.03)	-0.26 (0.06)	0.04 (0.03)	0.11 (0.03)	0.05 (0.03)	0.01 (0.03)	0 (0.01)	-0.03 (0.02)	0.03 (0.03)	0.08 (0.03)
	△ CV	-0.03	-0.07 (0.016)	-0.05 (0.001)	-0.06 (0.001)	0 (0.001)	0 (0.001)	0 (0)	-0.02 (0.016)	0 (0)	-0.01 (0.006)	-0.01 (0.009)	0.04 (0.016)
Slovenia	△ P90/P10	-0.04	-0.14 (0.07)	0.05 (0.07)	-0.77 (0.13)	0.68 (0.07)	0 (0.07)	0.14 (0.06)	-0.19 (0.06)	-0.07 (0.03)	-0.16 (0.05)	0.04 (0.04)	0.1 (0.07)
	△ P90/P50	0.02	0.02 (0.04)	0.11 (0.05)	0.15 (0.07)	0.23 (0.04)	-0.22 (0.04)	-0.05 (0.03)	-0.09 (0.03)	-0.03 (0.01)	-0.05 (0.03)	0 (0.02)	-0.01 (0.04)
	△ P90/P10	-0.06	-0.11 (0.04)	-0.08 (0.03)	-0.6 (0.07)	0.22 (0.03)	0.18 (0.03)	0.12 (0.03)	-0.02 (0.03)	-0.01 (0.01)	-0.04 (0.03)	0.03 (0.02)	0.05 (0.04)
	△ CV	-0.18	-0.17 (0.005)	-0.16 (0.003)	-0.12 (0.004)	0 (0.002)	-0.05 (0.002)	0.01 (0.001)	-0.01 (0.006)	-0.01 (0.002)	0 (0.003)	0.01 (0.003)	-0.01 (0.005)

Note: Decomposition result of Complete model in reverse order specified in equation (8). This corresponds to Table 11.

Table 16: Comaprison of coefficients between 1994 and 2012 (numeracy version)

	Complete model						Modified Mincer equation				Mincer equation			
	Numeracy		Years of education		Experience		Numeracy		Experience		Years of education		Experience	
Country	1994	2012	1994	2012	1994	2012	1994	2012	1994	2012	1994	2012	1994	2012
Belgium		0.568***		0.038***		0.022***		0.854***		0.022***		0.059***		0.024***
Chile	0.212***	0.299**	0.076***	0.088***	0.005	0.011	0.760***	0.866***	0.005	0.004	0.093***	0.105***	0.003	0.013**
Czech	0.054***	0.154***	0.031***	0.056***	0.018***	0.007	0.223***	0.605***	0.009	0.007	0.032***	0.061***	0.019***	0.008*
Denmark	0.259***	0.406***	0.034***	0.042***	0.034***	0.019***	0.540***	0.642***	0.037***	0.018***	0.04***	0.056***	0.035***	0.02***
Finland	0.387***	0.419***	0.018***	0.047***	0.019***	0.019***	0.514***	0.763***	0.018***	0.021***	0.024***	0.058***	0.019***	0.019***
France		0.355***		0.032***		0.02***		0.642***		0.019***		0.048***		0.02***
Ireland		0.699***		0.04***		0.022***		0.910***		0.021***		0.069***		0.024***
Italy	0.210***	0.235***	0.051***	0.052***	0.048***	0.034***	0.495***	0.636***	0.043***	0.027***	0.06***	0.061***	0.051***	0.035***
Japan		0.996***		0.038***		0.047***		1.310***		0.047***		0.066***		0.053***
Korea		0.587***		0.075***		0.031***		1.133***		0.031***		0.093***		0.03***
Netherlands		0.760***		0.06***		0.023***		1.183***		0.023***		0.087***		0.024***
Norway	0.251***	0.473***	0.026***	0.042***	0.017***	0.017***	0.472***	0.664***	0.005***	0.017***	0.031***	0.059***	0.019***	0.019***
Poland		0.415***		0.07***		0.024***		0.907***		0.021***		0.086***		0.023***
Slovenia	0.184***	0.436***	0.049***	0.086***	0.015**	0.014***	0.436***	0.647***	0.015**	0.008**	0.063***	0.113***	0.016**	0.014***
Spain		0.501***		0.06***		0.007*		0.222***		0.003		0.996***		0.008*
UK		0.889***		0.052***		0.032***		0.242***		0.031***		1.110***		0.036***

Note: Numeracy version of Figure 9Statistical significance at: ***1%, **5%, *10%.

Table 17: Results of decomposition for Complete model (numeracy ver.)

				Price Effects					Composition Effects				
	Inequality measures	Actual	Simulated actual	Total	Constant	Numeracy	Education	Experience	Total	Numeracy	Education	Experience	Residual
Czech	△ P90/P10	0.81	0.33 (0.06)	0.29 (0.06)	1.48 (0.14)	-0.52 (0.11)	-0.76 (0.09)	0.08 (0.06)	0.04 (0.04)	0.03 (0.01)	-0.01 (0.04)	0.03 (0.03)	0.48 (0.06)
	△ P90/P50	0.20	0.04 (0.03)	0.04 (0.03)	-0.06 (0.06)	0.1 (0.05)	-0.07 (0.03)	0.07 (0.03)	-0.01 (0.03)	0.01 (0.01)	-0.01 (0.02)	-0.01 (0.02)	0.16 (0.03)
	△ P90/P10	0.29	0.17 (0.02)	0.14 (0.02)	1.01 (0.08)	-0.46 (0.04)	-0.39 (0.05)	-0.02 (0.03)	0.03 (0.02)	0.01 (0.01)	0 (0.01)	0.03 (0.02)	0.12 (0.02)
	△ CV	-0.43	-0.52 (0.081)	-0.49 (0.007)	-0.44 (0.007)	-0.03 (0.001)	-0.02 (0.001)	0 (0)	-0.03 (0.08)	0.01 (0.001)	-0.06 (0.066)	0.02 (0.012)	0.09 (0.081)
Denmark	△ P90/P10	0.46	-0.04 (0.05)	-0.12 (0.06)	-0.63 (0.08)	0.16 (0.05)	0.21 (0.04)	0.15 (0.04)	0.08 (0.05)	0.03 (0.02)	-0.05 (0.04)	0.09 (0.05)	0.5 (0.05)
	△ P90/P50	0.10	0.03 (0.02)	0.03 (0.03)	-0.21 (0.04)	0.07 (0.02)	0.09 (0.02)	0.07 (0.02)	0 (0.02)	0 (0.01)	-0.02 (0.02)	0.01 (0.02)	0.07 (0.02)
	△ P90/P10	0.19	-0.06 (0.03)	-0.11 (0.04)	-0.23 (0.06)	0.03 (0.03)	0.06 (0.02)	0.03 (0.03)	0.05 (0.03)	0.02 (0.01)	-0.01 (0.02)	0.04 (0.03)	0.25 (0.03)
	△ CV	-0.01	-0.05 (0.001)	-0.06 (0.001)	-0.06 (0.001)	0 (0)	0 (0)	0.01 (0.001)	0.01 (0.002)	0 (0.001)	0 (0.001)	0.01 (0.002)	0.04 (0.001)
Finland	△ P90/P10	0.25	0.04 (0.06)	-0.08 (0.06)	-0.86 (0.09)	0.39 (0.04)	0.13 (0.06)	0.25 (0.04)	0.12 (0.04)	0.02 (0.02)	-0.02 (0.02)	0.13 (0.04)	0.21 (0.06)
	△ P90/P50	0.23	0.14 (0.02)	0.12 (0.03)	-0.34 (0.05)	0.18 (0.03)	0.15 (0.03)	0.13 (0.02)	0.02 (0.02)	0 (0.01)	-0.01 (0.01)	0.03 (0.01)	0.09 (0.02)
	△ P90/P10	-0.07	-0.13 (0.04)	-0.19 (0.04)	-0.24 (0.05)	0.08 (0.02)	-0.06 (0.04)	0.03 (0.02)	0.06 (0.03)	0.01 (0.01)	0 (0.02)	0.06 (0.03)	-0.57 (0.04)
	△ CV	0.05	0.03 (0.002)	0.03 (0.001)	0.02 (0.002)	0.01 (0.001)	-0.01 (0.001)	0.01 (0.001)	0 (0.001)	0 (0)	0 (0)	0 (0.001)	0.01 (0.002)
Italy	△ P90/P10	0.53	0.06 (0.11)	0.09 (0.09)	2.58 (0.22)	-3.16 (0.2)	0.26 (0.07)	0.41 (0.08)	-0.03 (0.1)	-0.03 (0.05)	-0.09 (0.08)	0.07 (0.06)	0.47 (0.11)
	△ P90/P50	0.24	0.09 (0.05)	0.11 (0.04)	0.51 (0.08)	-0.5 (0.06)	0.02 (0.04)	0.08 (0.03)	-0.02 (0.04)	0 (0.01)	-0.03 (0.04)	0.02 (0.02)	0.15 (0.05)
	△ P90/P10	0.06	-0.05 (0.04)	-0.05 (0.04)	0.66 (0.09)	-0.99 (0.07)	0.13 (0.03)	0.16 (0.04)	0 (0.04)	-0.01 (0.03)	-0.02 (0.03)	0.03 (0.03)	0.11 (0.04)
	△ CV	-0.02	-0.03 (0.004)	-0.03 (0.003)	0.08 (0.003)	-0.12 (0.002)	0 (0.002)	0.02 (0.002)	0 (0.004)	0 (0.001)	0 (0.002)	0 (0.003)	0.01 (0.004)
Norway	△ P90/P10	0.35	0.1 (0.07)	0.13 (0.06)	-0.3 (0.08)	-0.2 (0.06)	0.44 (0.05)	0.2 (0.04)	-0.03 (0.05)	-0.01 (0.01)	-0.08 (0.03)	0.05 (0.04)	0.25 (0.07)
	△ P90/P50	0.19	0.1 (0.03)	0.11 (0.03)	-0.16 (0.04)	0.02 (0.03)	0.17 (0.02)	0.08 (0.02)	-0.01 (0.02)	0 (0.01)	-0.01 (0.01)	0 (0.01)	0.09 (0.03)
	△ P90/P10	0.03	-0.03 (0.04)	-0.02 (0.03)	-0.06 (0.04)	-0.15 (0.03)	0.13 (0.03)	0.06 (0.02)	-0.01 (0.03)	-0.01 (0.01)	-0.04 (0.02)	0.03 (0.03)	0.06 (0.04)
	△ CV	-0.03	-0.07 (0.014)	-0.05 (0.001)	-0.05 (0.001)	-0.01 (0.001)	0 (0)	0 (0)	-0.02 (0.014)	0 (0)	-0.01 (0.006)	-0.01 (0.008)	0.04 (0.014)
Slovenia	△ P90/P10	-0.04	-0.11 (0.06)	0.07 (0.06)	-0.71 (0.1)	0.79 (0.05)	-0.14 (0.06)	0.12 (0.05)	-0.18 (0.06)	-0.03 (0.02)	-0.15 (0.05)	0.03 (0.04)	0.07 (0.06)
	△ P90/P50	0.02	0.02 (0.03)	0.1 (0.03)	0.03 (0.06)	0.28 (0.03)	-0.17 (0.04)	-0.05 (0.03)	-0.08 (0.03)	-0.01 (0.01)	-0.05 (0.03)	-0.01 (0.01)	0 (0.03)
	△ P90/P10	-0.06	-0.09 (0.03)	-0.06 (0.03)	-0.48 (0.06)	0.24 (0.03)	0.07 (0.03)	0.11 (0.03)	-0.03 (0.03)	-0.01 (0.01)	-0.04 (0.02)	0.03 (0.02)	0.03 (0.03)
	△ CV	-0.18	-0.17 (0.005)	-0.16 (0.003)	-0.13 (0.003)	0.01 (0.003)	-0.05 (0.002)	0.01 (0.001)	-0.01 (0.004)	-0.01 (0.002)	0 (0.002)	0.01 (0.002)	-0.01 (0.005)

Note: Complete model version of the previous table.

Table 18: Results of decomposition for Complete model in reverse order (numeracy ver.)

				Price Effects					Composition Effects				
	Inequality measures	Actual	Simulated actual	Total	Constant	Numeracy	Education	Experience	Total	Numeracy	Education	Experience	Residual
Czech	△ P90/P10	0.81	0.33 (0.06)	0.29 (0.06)	1.48 (0.14)	-0.52 (0.11)	-0.76 (0.09)	0.08 (0.06)	0.04 (0.04)	0.03 (0.01)	-0.01 (0.04)	0.03 (0.03)	0.48 (0.06)
	△ P90/P50	0.20	0.04 (0.03)	0.04 (0.03)	-0.06 (0.06)	0.1 (0.05)	-0.07 (0.03)	0.07 (0.03)	-0.01 (0.03)	0.01 (0.01)	-0.01 (0.02)	-0.01 (0.02)	0.16 (0.03)
	△ P90/P10	0.29	0.17 (0.02)	0.14 (0.02)	1.01 (0.08)	-0.46 (0.04)	-0.39 (0.05)	-0.02 (0.03)	0.03 (0.02)	0.01 (0.01)	0 (0.01)	0.03 (0.02)	0.12 (0.02)
	△ CV	-0.43	-0.52 (0.081)	-0.49 (0.007)	-0.44 (0.007)	-0.03 (0.001)	-0.02 (0.001)	0 (0)	-0.03 (0.08)	0.01 (0.001)	-0.06 (0.066)	0.02 (0.012)	0.09 (0.081)
Denmark	△ P90/P10	0.46	-0.04 (0.05)	-0.12 (0.06)	-0.63 (0.08)	0.16 (0.05)	0.21 (0.04)	0.15 (0.04)	0.08 (0.05)	0.03 (0.02)	-0.05 (0.04)	0.09 (0.05)	0.5 (0.05)
	△ P90/P50	0.10	0.03 (0.02)	0.03 (0.03)	-0.21 (0.04)	0.07 (0.02)	0.09 (0.02)	0.07 (0.02)	0 (0.02)	0 (0.01)	-0.02 (0.02)	0.01 (0.02)	0.07 (0.02)
	△ P90/P10	0.19	-0.06 (0.03)	-0.11 (0.04)	-0.23 (0.06)	0.03 (0.03)	0.06 (0.02)	0.03 (0.03)	0.05 (0.03)	0.02 (0.01)	-0.01 (0.02)	0.04 (0.03)	0.25 (0.03)
	△ CV	-0.01	-0.05 (0.001)	-0.06 (0.001)	-0.06 (0.001)	0 (0)	0 (0)	0.01 (0.001)	0.01 (0.002)	0 (0.001)	0 (0.001)	0.01 (0.002)	0.04 (0.001)
Finland	△ P90/P10	0.25	0.04 (0.06)	-0.08 (0.06)	-0.86 (0.09)	0.39 (0.04)	0.13 (0.06)	0.25 (0.04)	0.12 (0.04)	0.02 (0.02)	-0.02 (0.02)	0.13 (0.04)	0.21 (0.06)
	△ P90/P50	0.23	0.14 (0.02)	0.12 (0.03)	-0.34 (0.05)	0.18 (0.03)	0.15 (0.03)	0.13 (0.02)	0.02 (0.02)	0 (0.01)	-0.01 (0.01)	0.03 (0.01)	0.09 (0.02)
	△ P90/P10	-0.07	-0.13 (0.04)	-0.19 (0.04)	-0.24 (0.05)	0.08 (0.02)	-0.06 (0.04)	0.03 (0.02)	0.06 (0.03)	0.01 (0.01)	0 (0.02)	0.06 (0.03)	-0.57 (0.04)
	△ CV	0.05	0.03 (0.002)	0.03 (0.001)	0.02 (0.002)	0.01 (0.001)	-0.01 (0.001)	0.01 (0.001)	0 (0.001)	0 (0)	0 (0)	0 (0.001)	0.01 (0.002)
Italy	△ P90/P10	0.53	0.06 (0.11)	0.09 (0.09)	2.58 (0.22)	-3.16 (0.2)	0.26 (0.07)	0.41 (0.08)	-0.03 (0.1)	-0.03 (0.05)	-0.09 (0.08)	0.07 (0.06)	0.47 (0.11)
	△ P90/P50	0.24	0.09 (0.05)	0.11 (0.04)	0.51 (0.08)	-0.5 (0.06)	0.02 (0.04)	0.08 (0.03)	-0.02 (0.04)	0 (0.01)	-0.03 (0.04)	0.02 (0.02)	0.15 (0.05)
	△ P90/P10	0.06	-0.05 (0.04)	-0.05 (0.04)	0.66 (0.09)	-0.99 (0.07)	0.13 (0.03)	0.16 (0.04)	0 (0.04)	-0.01 (0.03)	-0.02 (0.03)	0.03 (0.03)	0.11 (0.04)
	△ CV	-0.02	-0.03 (0.004)	-0.03 (0.003)	0.08 (0.003)	-0.12 (0.002)	0 (0.002)	0.02 (0.002)	0 (0.004)	0 (0.001)	0 (0.002)	0 (0.003)	0.01 (0.004)
Norway	△ P90/P10	0.35	0.1 (0.07)	0.13 (0.06)	-0.3 (0.08)	-0.2 (0.06)	0.44 (0.05)	0.2 (0.04)	-0.03 (0.05)	-0.01 (0.01)	-0.08 (0.03)	0.05 (0.04)	0.25 (0.07)
	△ P90/P50	0.19	0.1 (0.03)	0.11 (0.03)	-0.16 (0.04)	0.02 (0.03)	0.17 (0.02)	0.08 (0.02)	-0.01 (0.02)	0 (0.01)	-0.01 (0.01)	0 (0.01)	0.09 (0.03)
	△ P90/P10	0.03	-0.03 (0.04)	-0.02 (0.03)	-0.06 (0.04)	-0.15 (0.03)	0.13 (0.03)	0.06 (0.02)	-0.01 (0.03)	-0.01 (0.01)	-0.04 (0.02)	0.03 (0.03)	0.06 (0.04)
	△ CV	-0.03	-0.07 (0.014)	-0.05 (0.001)	-0.05 (0.001)	-0.01 (0.001)	0 (0)	0 (0)	-0.02 (0.014)	0 (0)	-0.01 (0.006)	-0.01 (0.008)	0.04 (0.014)
Slovenia	△ P90/P10	-0.04	-0.11 (0.06)	0.07 (0.06)	-0.71 (0.1)	0.79 (0.05)	-0.14 (0.06)	0.12 (0.05)	-0.18 (0.06)	-0.03 (0.02)	-0.15 (0.05)	0.03 (0.04)	0.07 (0.06)
	△ P90/P50	0.02	0.02 (0.03)	0.1 (0.03)	0.03 (0.06)	0.28 (0.03)	-0.17 (0.04)	-0.05 (0.03)	-0.08 (0.03)	-0.01 (0.01)	-0.05 (0.03)	-0.01 (0.01)	0 (0.03)
	△ P90/P10	-0.06	-0.09 (0.03)	-0.06 (0.03)	-0.48 (0.06)	0.24 (0.03)	0.07 (0.03)	0.11 (0.03)	-0.03 (0.03)	-0.01 (0.01)	-0.04 (0.02)	0.03 (0.02)	0.03 (0.03)
	△ CV	-0.18	-0.17 (0.005)	-0.16 (0.003)	-0.13 (0.003)	0.01 (0.003)	-0.05 (0.002)	0.01 (0.001)	-0.01 (0.004)	-0.01 (0.002)	0 (0.002)	0.01 (0.002)	-0.01 (0.005)

Note: Decomposition result of Complete model in reverse order specified in equation (8). This corresponds to Table 11.

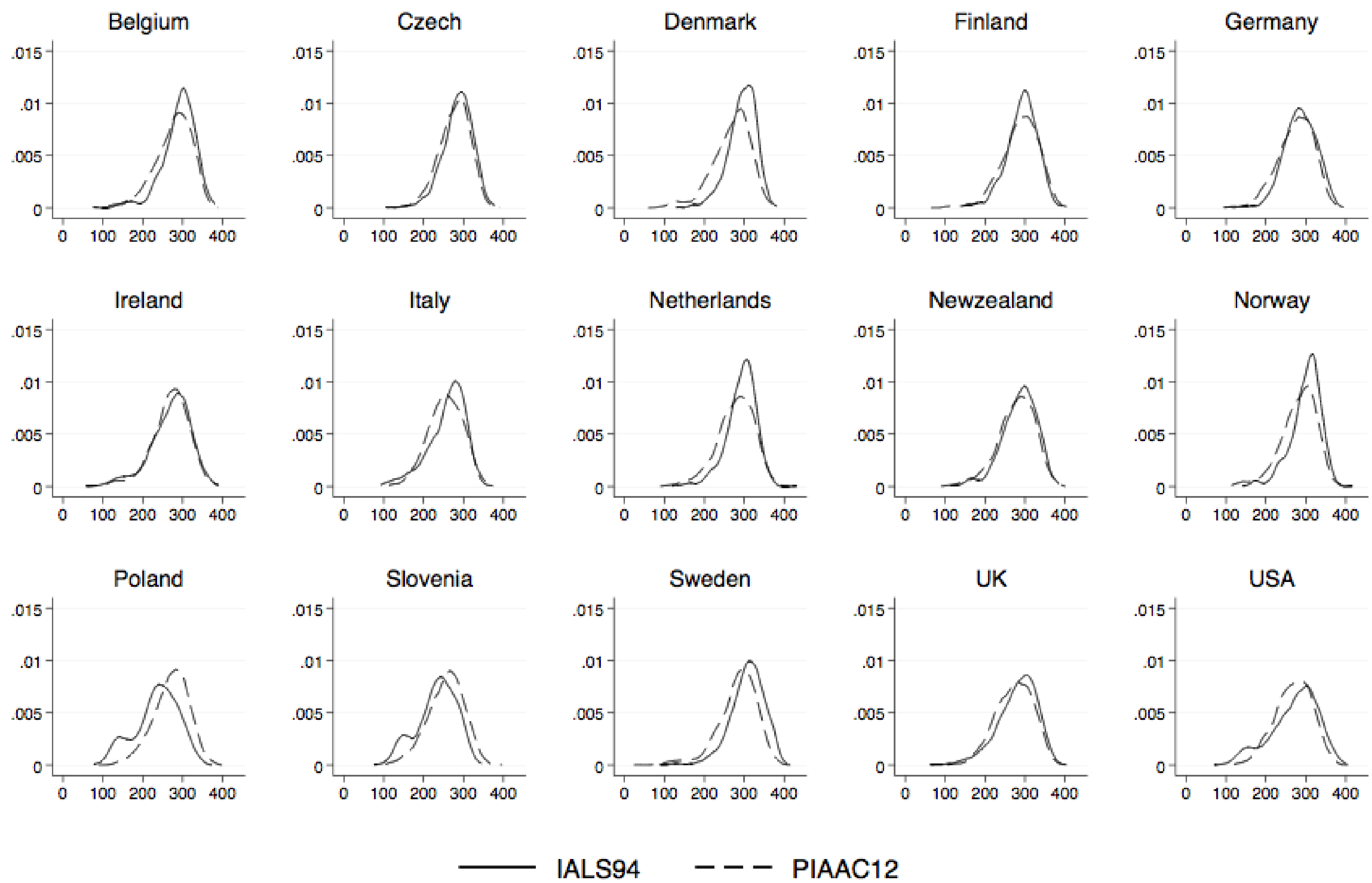
Table 19: Result of marginal effect analysis for Complete model (numeracy ver.)

				Price Effects					Composition Effects			
	Inequality measures	Actual	Simulated actual	Total	Constant	Numeracy	Education	Experience	Total	Numeracy	Education	Experience
Czech	P90/P10 in 2012	3.09	2.56 (0.08)	-0.29 (0.06)	-0.16 (0.08)	0.52 (0.11)	0.76 (0.09)	-0.08 (0.06)	-0.02 (0.05)	-0.07 (0.03)	0.04 (0.06)	0.01 (0.03)
	P90/P50 in 2012	1.78	1.59 (0.04)	-0.04 (0.03)	0.08 (0.04)	-0.1 (0.05)	0.07 (0.03)	-0.07 (0.03)	0.04 (0.03)	0.01 (0.01)	0.02 (0.03)	0.01 (0.02)
	P50/P10 in 2012	1.73	1.61 (0.03)	-0.14 (0.02)	-0.17 (0.04)	0.46 (0.04)	0.39 (0.05)	0.02 (0.03)	-0.05 (0.03)	-0.05 (0.02)	0 (0.03)	-0.01 (0.02)
	CV in 2012	0.13	0.08 (0.002)	0.49 (0.007)	0.34 (0.005)	0.03 (0.001)	0.02 (0.001)	0 (0)	0.01 (0.012)	0 (0)	0.01 (0.012)	0 (0)
Denmark	P90/P10 in 2012	2.75	2.19 (0.05)	0.12 (0.06)	1.02 (0.07)	-0.16 (0.05)	-0.21 (0.04)	-0.15 (0.04)	0.02 (0.05)	-0.03 (0.02)	0.08 (0.04)	-0.02 (0.02)
	P90/P50 in 2012	1.64	1.51 (0.03)	-0.03 (0.03)	0.1 (0.03)	-0.07 (0.02)	-0.09 (0.02)	-0.07 (0.02)	0.02 (0.03)	0 (0.01)	0.03 (0.02)	-0.01 (0.01)
	P50/P10 in 2012	1.67	1.45 (0.03)	0.11 (0.04)	0.55 (0.04)	-0.03 (0.03)	-0.06 (0.02)	-0.03 (0.03)	0 (0.02)	-0.02 (0.01)	0.02 (0.02)	0 (0.01)
	CV in 2012	0.11	0.06 (0.001)	0.06 (0.001)	0.09 (0.001)	0 (0)	0 (0)	-0.01 (0.001)	0 (0.001)	0 (0)	0 (0.001)	0 (0)
Finland	P90/P10 in 2012	2.62	2.37 (0.06)	0.08 (0.06)	1.26 (0.09)	-0.39 (0.04)	-0.13 (0.06)	-0.25 (0.04)	0.04 (0.05)	-0.01 (0.02)	0.08 (0.05)	-0.02 (0.03)
	P90/P50 in 2012	1.68	1.54 (0.03)	-0.12 (0.03)	0.54 (0.04)	-0.18 (0.03)	-0.15 (0.03)	-0.13 (0.02)	0.01 (0.03)	-0.01 (0.01)	0.03 (0.02)	-0.01 (0.02)
	P50/P10 in 2012	1.56	1.54 (0.04)	0.19 (0.04)	0.2 (0.04)	-0.08 (0.02)	0.06 (0.04)	-0.03 (0.02)	0.01 (0.02)	0 (0.01)	0.02 (0.02)	-0.01 (0.02)
	CV in 2012	0.13	0.11 (0.002)	-0.03 (0.001)	-0.01 (0.001)	-0.01 (0.001)	0.01 (0.001)	-0.01 (0.001)	0 (0.002)	0 (0)	0.01 (0.001)	0 (0)
Italy	P90/P10 in 2012	3.60	3.1 (0.09)	-0.09 (0.09)	-0.87 (0.08)	3.16 (0.2)	-0.26 (0.07)	-0.41 (0.08)	0.04 (0.11)	-0.05 (0.04)	0.14 (0.09)	-0.03 (0.05)
	P90/P50 in 2012	2.08	1.84 (0.04)	-0.11 (0.04)	-0.4 (0.04)	0.5 (0.06)	-0.02 (0.04)	-0.08 (0.03)	0.02 (0.05)	-0.02 (0.01)	0.05 (0.05)	-0.01 (0.02)
	P50/P10 in 2012	1.73	1.68 (0.05)	0.05 (0.04)	-0.14 (0.04)	0.99 (0.07)	-0.13 (0.03)	-0.16 (0.04)	0.01 (0.03)	-0.01 (0.02)	0.03 (0.03)	-0.01 (0.02)
	CV in 2012	0.20	0.17 (0.003)	0.03 (0.003)	-0.02 (0.003)	0.12 (0.002)	0 (0.002)	-0.02 (0.002)	0 (0.003)	0 (0.002)	0 (0.002)	0 (0.001)
Norway	P90/P10 in 2012	2.67	2.3 (0.07)	-0.13 (0.06)	0.42 (0.06)	0.2 (0.06)	-0.44 (0.05)	-0.2 (0.04)	0.1 (0.07)	-0.03 (0.02)	0.09 (0.05)	0.03 (0.04)
	P90/P50 in 2012	1.65	1.54 (0.04)	-0.11 (0.03)	0.14 (0.03)	-0.02 (0.03)	-0.17 (0.02)	-0.08 (0.02)	0.04 (0.03)	-0.01 (0.01)	0.04 (0.03)	0.02 (0.02)
	P50/P10 in 2012	1.62	1.5 (0.03)	0.02 (0.03)	0.12 (0.03)	0.15 (0.03)	-0.13 (0.03)	-0.06 (0.02)	0.02 (0.03)	-0.01 (0.01)	0.02 (0.02)	0.01 (0.02)
	CV in 2012	0.09	0.06 (0.001)	0.05 (0.001)	0.05 (0.001)	0.01 (0.001)	0 (0)	0 (0)	0.02 (0.012)	0 (0)	0.01 (0.008)	0.01 (0.005)
Slovenia	P90/P10 in 2012	2.88	2.68 (0.06)	-0.07 (0.06)	1.62 (0.14)	-0.79 (0.05)	0.14 (0.06)	-0.12 (0.05)	0.4 (0.09)	0.07 (0.03)	0.3 (0.07)	0.01 (0.02)
	P90/P50 in 2012	1.83	1.7 (0.04)	-0.1 (0.03)	-0.03 (0.04)	-0.28 (0.03)	0.17 (0.04)	0.05 (0.03)	0.11 (0.05)	0.02 (0.02)	0.07 (0.04)	0 (0.02)
	P50/P10 in 2012	1.58	1.57 (0.03)	0.06 (0.03)	1 (0.08)	-0.24 (0.03)	-0.07 (0.03)	-0.11 (0.03)	0.12 (0.04)	0.02 (0.02)	0.1 (0.04)	0 (0.01)
	CV in 2012	0.21	0.19 (0.004)	0.16 (0.003)	0.13 (0.002)	-0.01 (0.003)	0.05 (0.002)	-0.01 (0.001)	0.02 (0.004)	0.01 (0.001)	0.02 (0.003)	0 (0)

Note: Complete model version of the previous table.

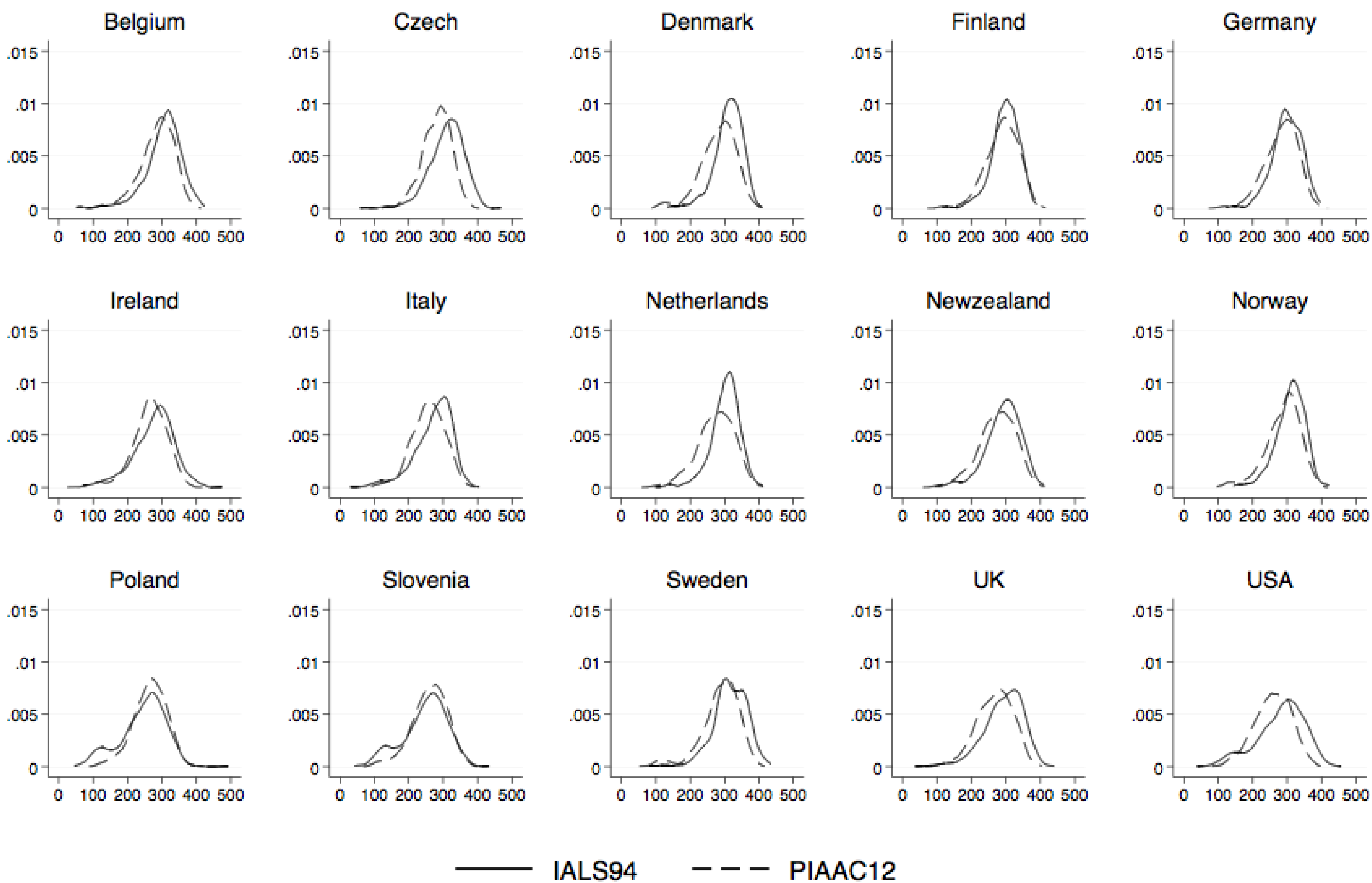
Figures

Figure 1: Literacy distributions: IALS94 vs PIAAC12



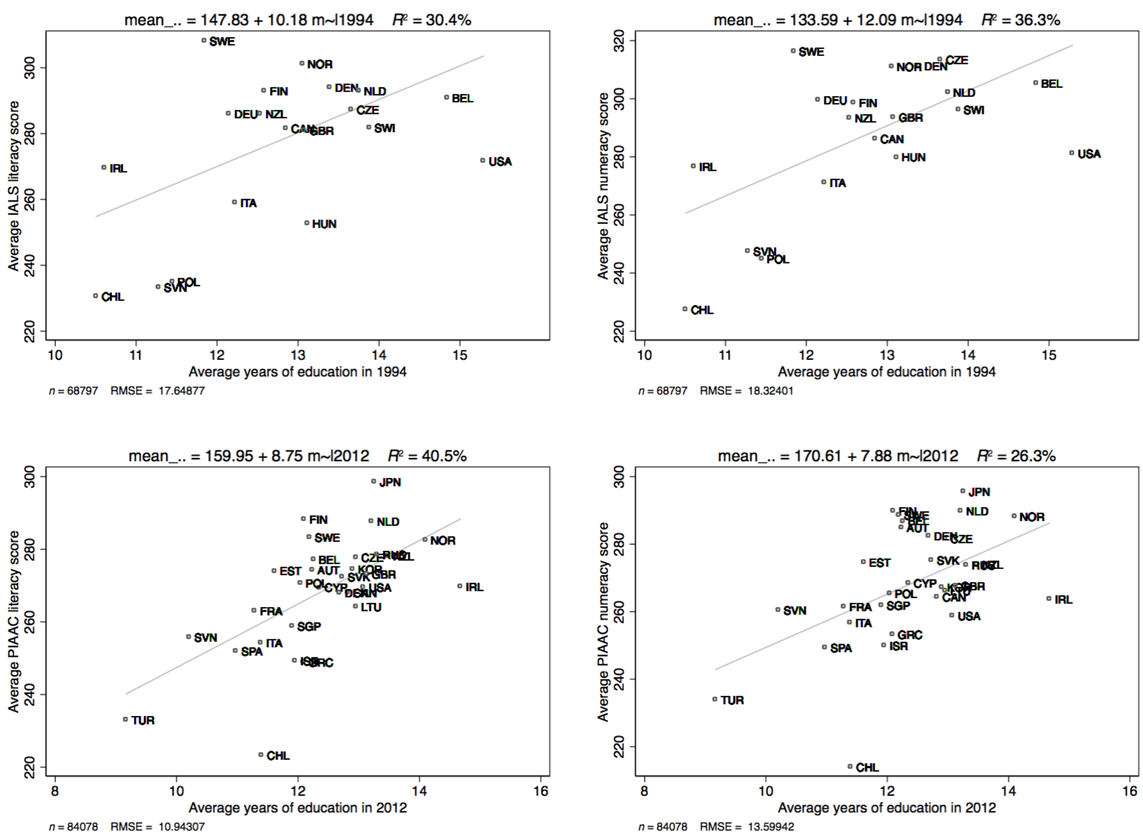
Note: Kernel density estimation of IALS and PIAAC literacy scores by country

Figure 2: Numeracy distributions: IALS94 vs PIAAC12



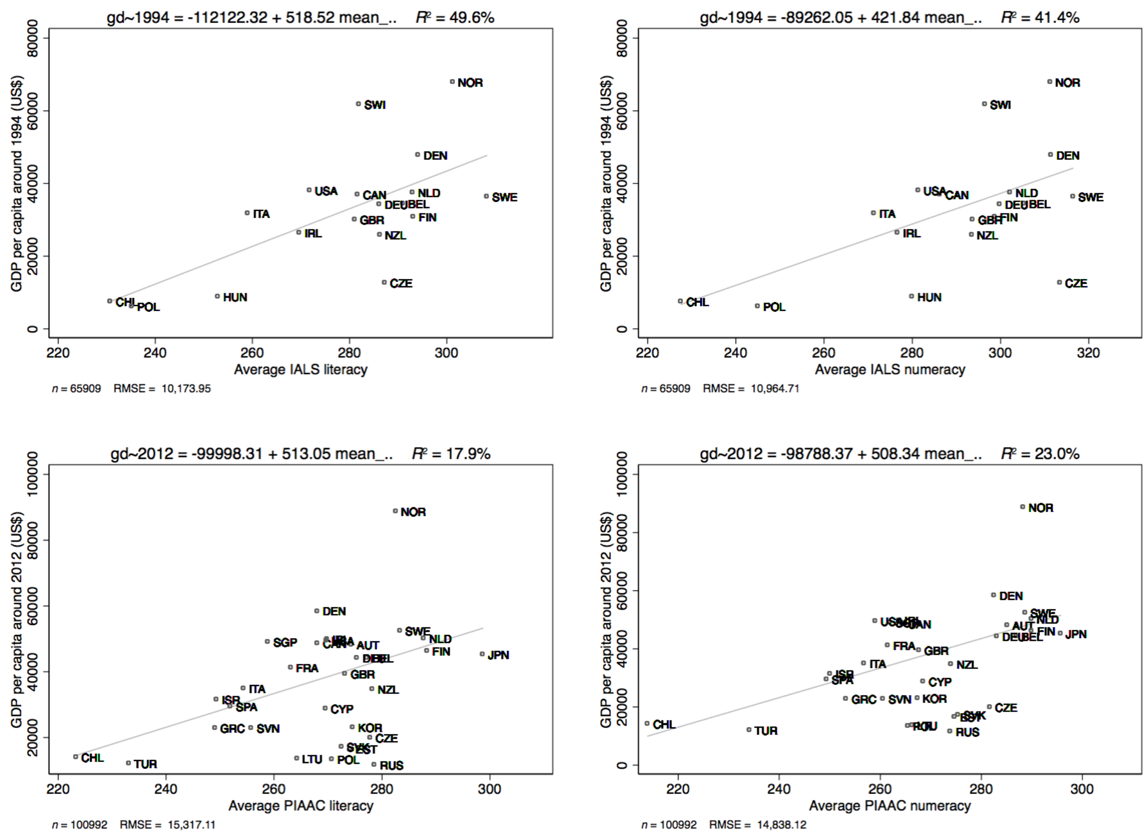
Note: Kernel density estimation of IALS and PIAAC numeracy scores by country

Figure 3: Cognitive skills and years of education



Note: X-axis is average years of education and Y-axis is average literacy (left) and numeracy (right). Top 2 graphs are of IALS and 1994. Bottom 2 graphs are of PIAAC and 2012.

Figure 4: GDP per capita and cognitive skills

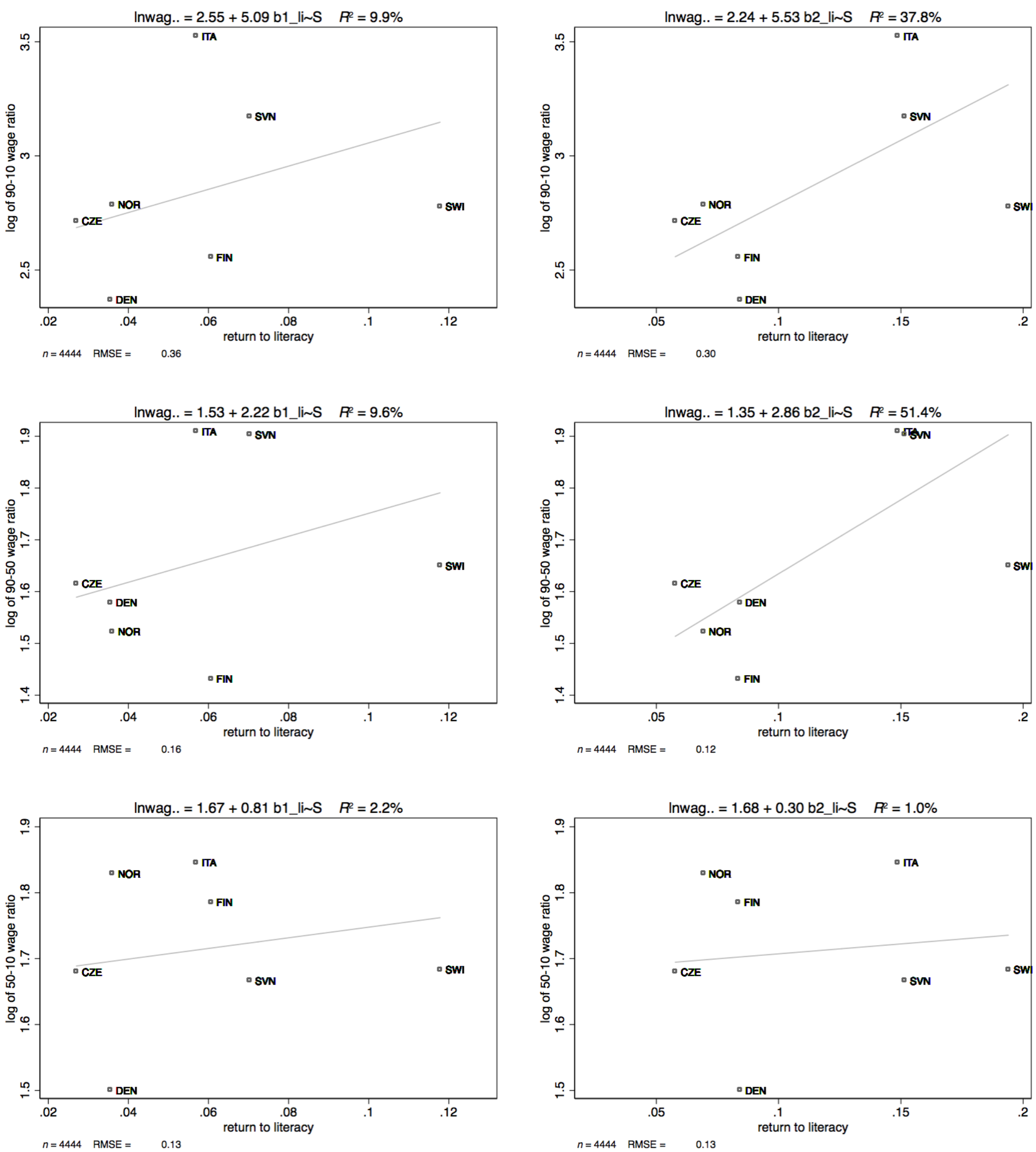


Note: X-axis is average literacy scores (left) and numeracy scores (right), and Y-axis represents GDP per capita. Top 2 graphs are of IALS and 1994. Bottom 2 graphs are of PIAAC and 2012.

Figure 5: Return to literacy skills

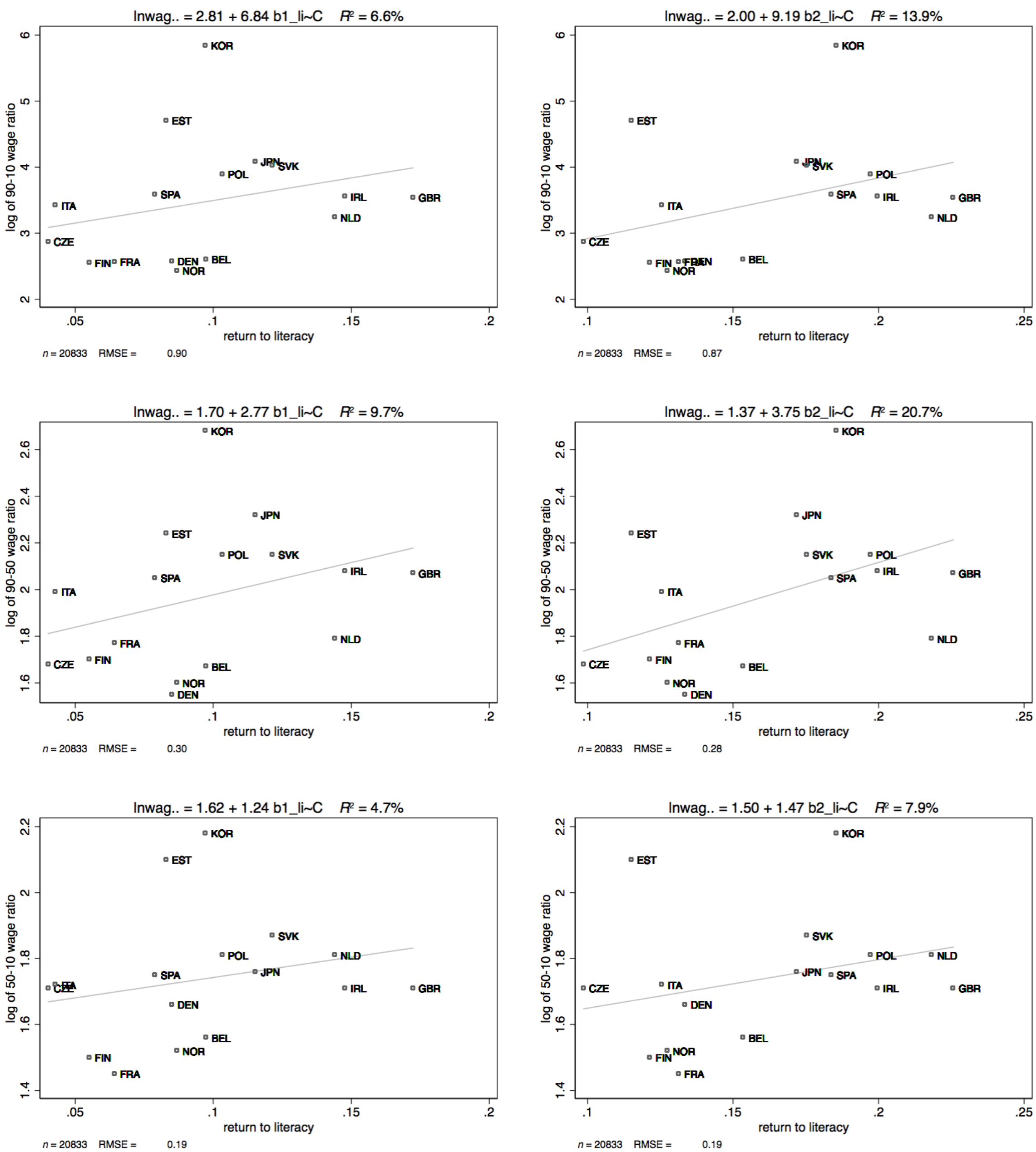
Note: Each bar represents a coefficient on cognitive skills (literacy/numeracy) on log hourly wage. ”with education” refers to the specification where regressors include cognitive skills, years of education, experience and squared experience. ”without education” refers to the specification without years of education.

Figure 6: Return to IALS score and wage inequality in 1994



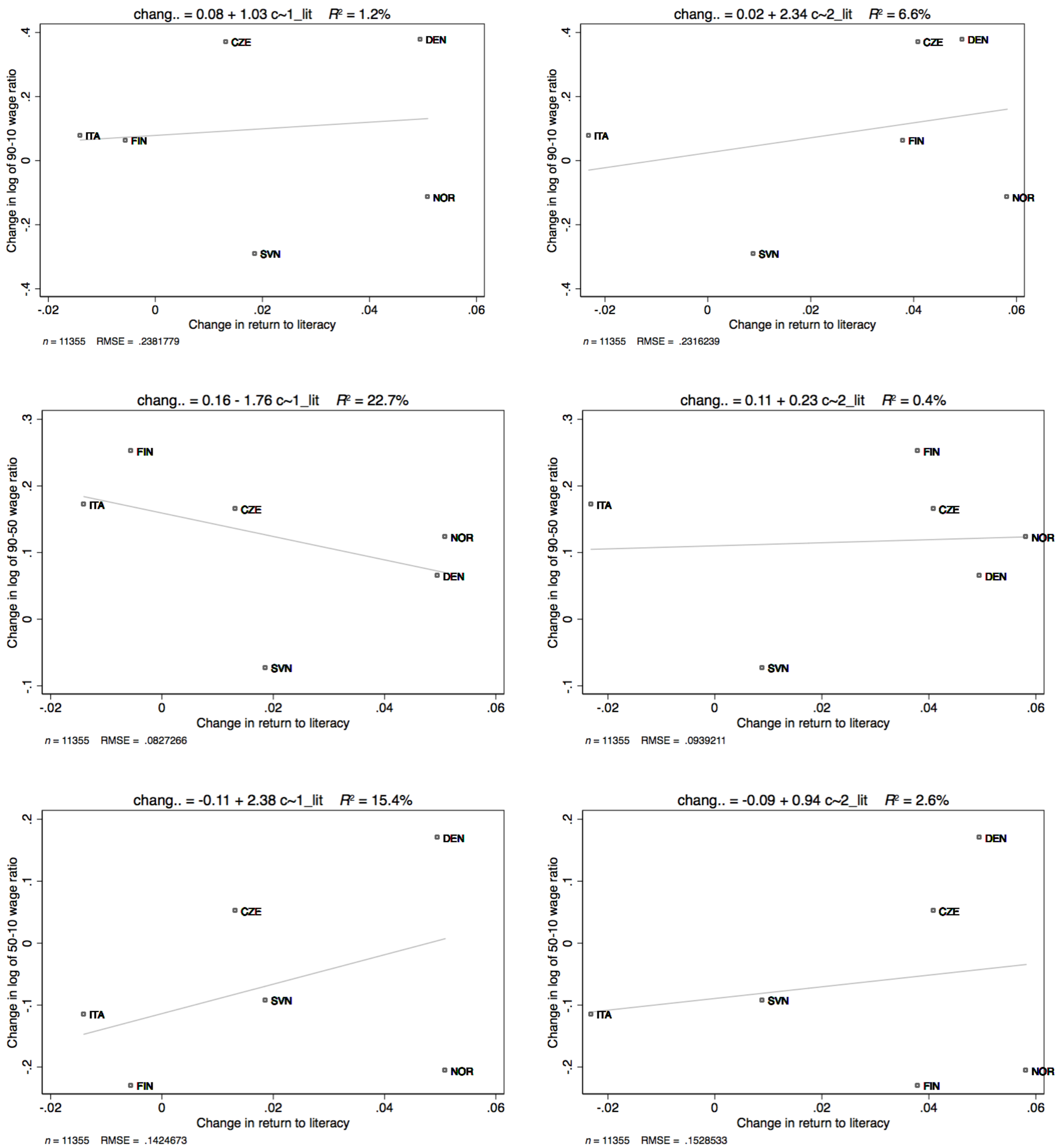
Note: Each box shows a relationshp between coefficient of literacy and wage inequalities in 1994. From the top, inequality measures are 90-10 wage ratio, 90-50 wage ratio and 50-10 wage ratio. Left figures use coefficient of literacy in the Mincer model (i.e. not controlling for education) and right figures use coefficient from Complete model (i.e. controlling for education). Outside each box, fit of linear relationship as well as R^2 are reported.

Figure 7: Return to PIAAC score and wage inequality in 2012



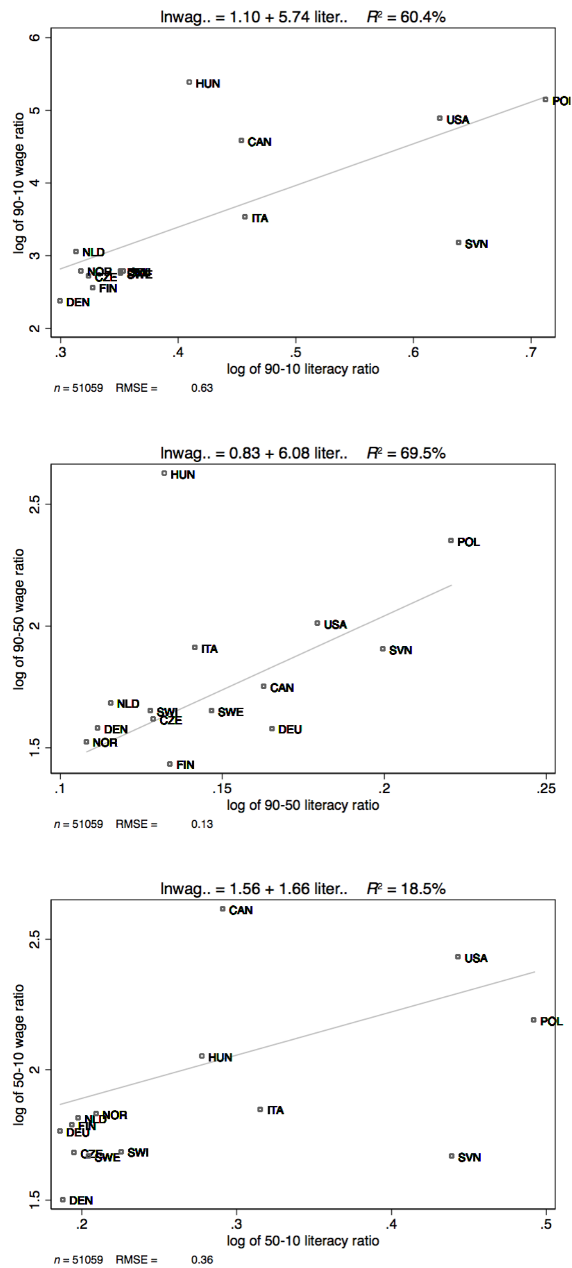
Note: 2012 version of the previous table.

Figure 8: Change in return to literacy score and change in wage inequality



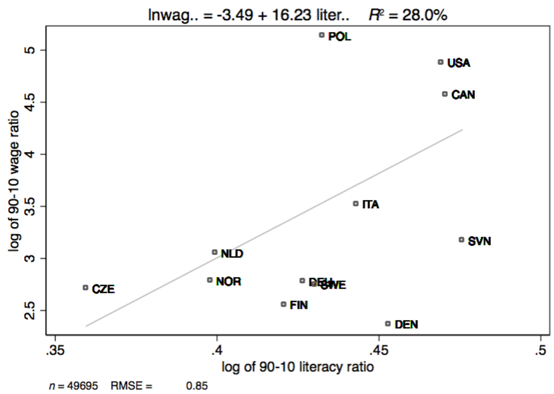
Note: X-axis represents change in return to literacy, whereas Y-axis is change in inequality measures.

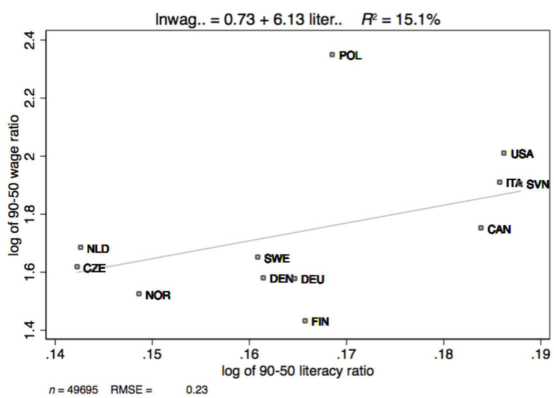
Figure 9: Relationship between IALS score inequality and wage inequality in 1994

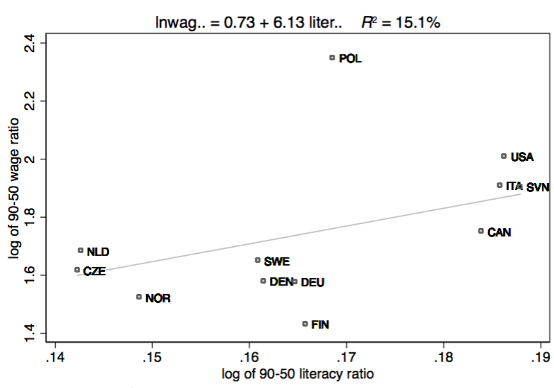


Note: Each box plots the relationship between log of wage ratio and log of literacy ratio (90-10, 90-50 and 50-10 percentile ratios) in 1994. Log of wage ratio comes from values reported in Leuven et al. (2004) cauclated using fulltime worker samples. Outside each box, fit of linear relationship as well as R^2 are reported.

Figure 10: Relationship between PIAAC score inequality and wage inequality in 2012

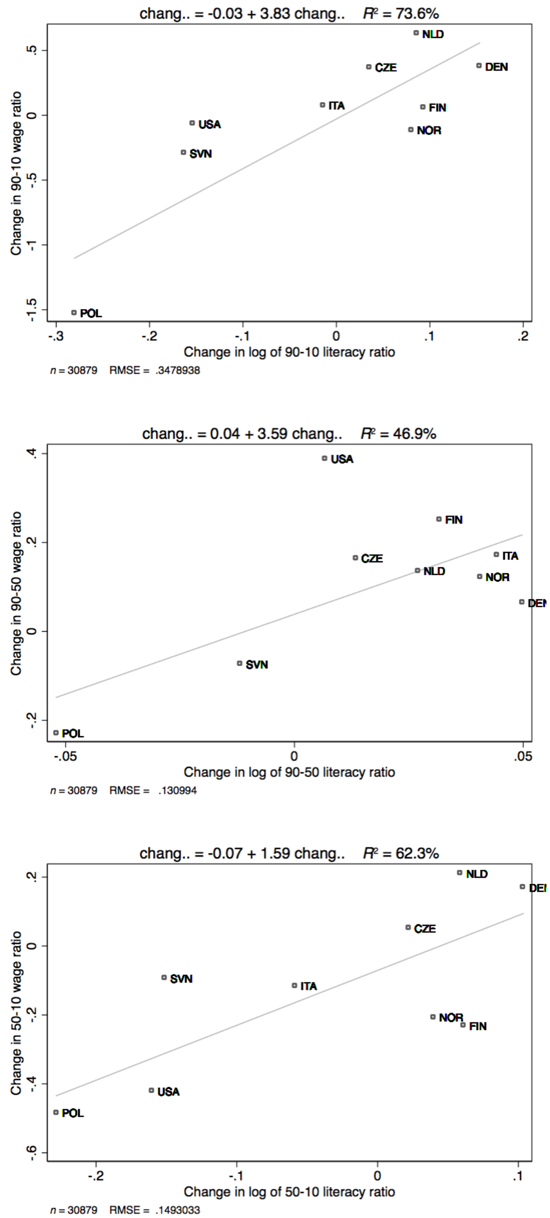






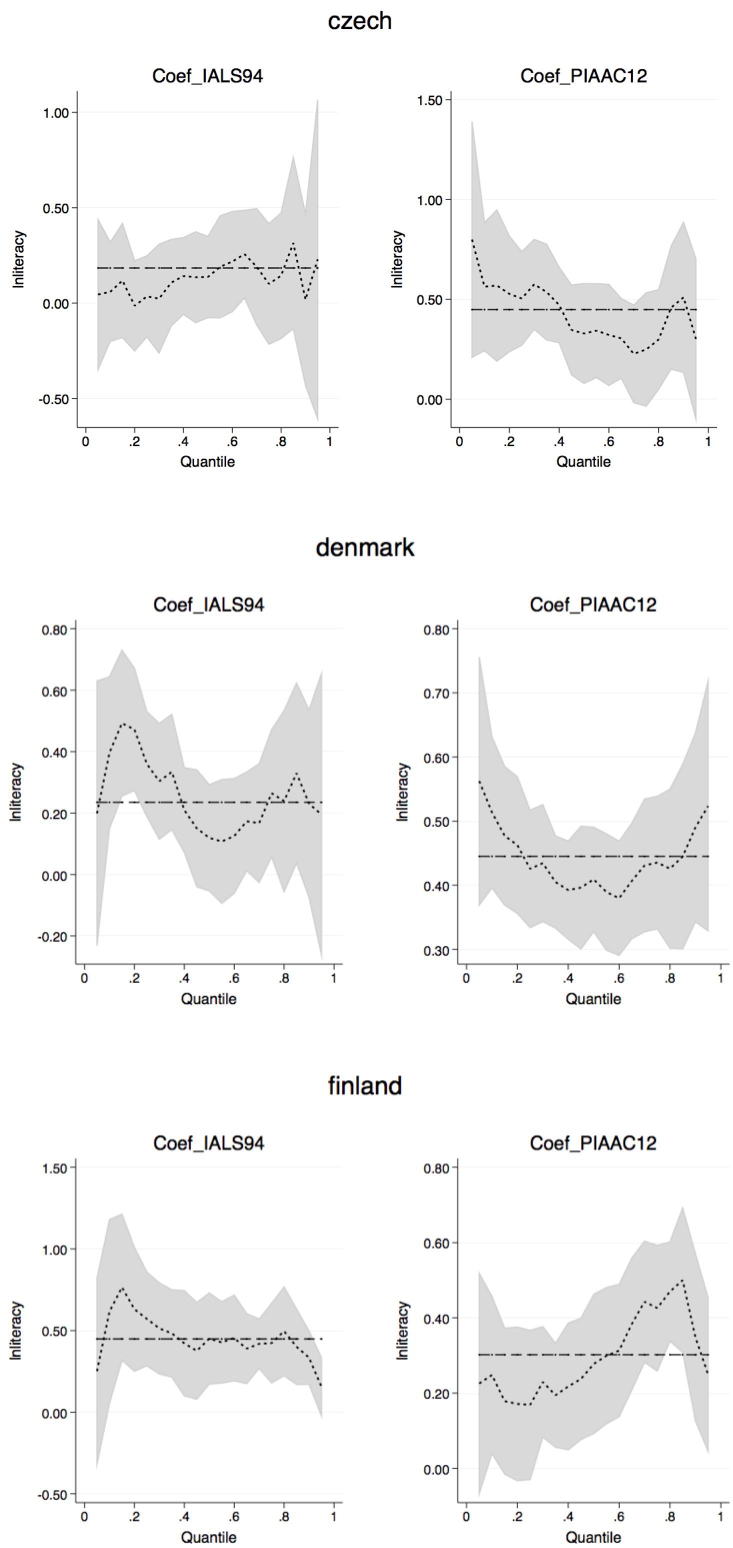
Note: 2012 version of the previous figure. Values of wage inequality in the US comes from Broecke et al. (2018), but for all other countries the values are the author's calculation using PIAAC.

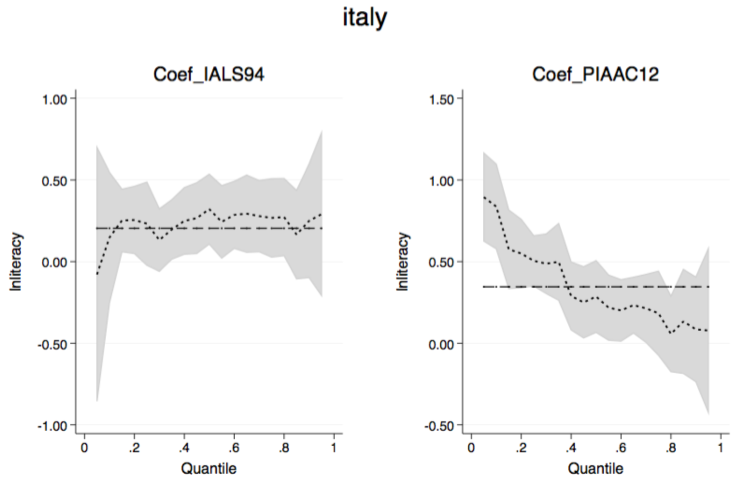
Figure 11: Relationship between change in inequality of test scores and change inequality of wages (from 1994 to 2012)

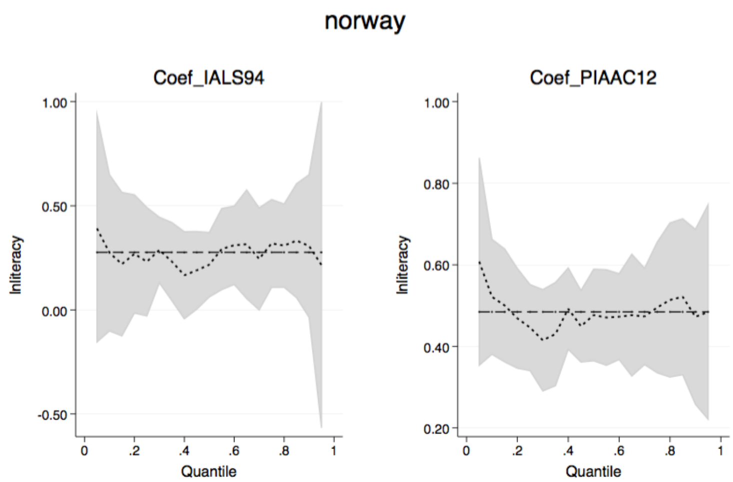


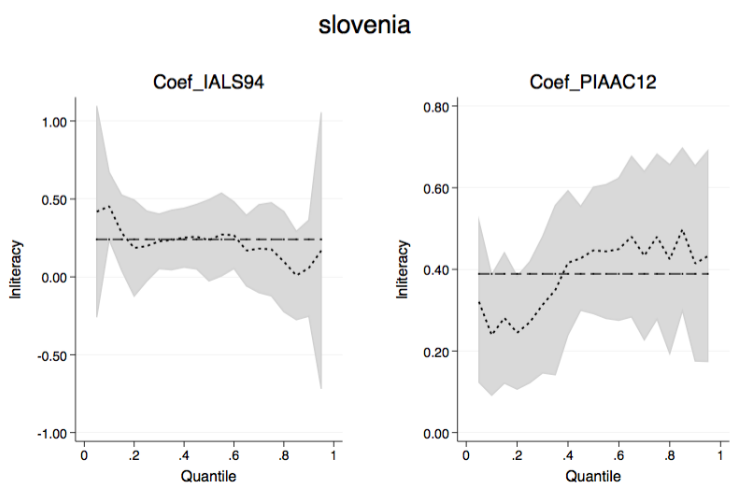
Note: X-axis represnts the change in log of literacy ratio, whereas Y-axis shows the change in log of wage ratio. Change in wage ratio uses "LOV" values in Table 8.

Figure 11: Quantile regression coefficients of literacy in 1994 and in 2012



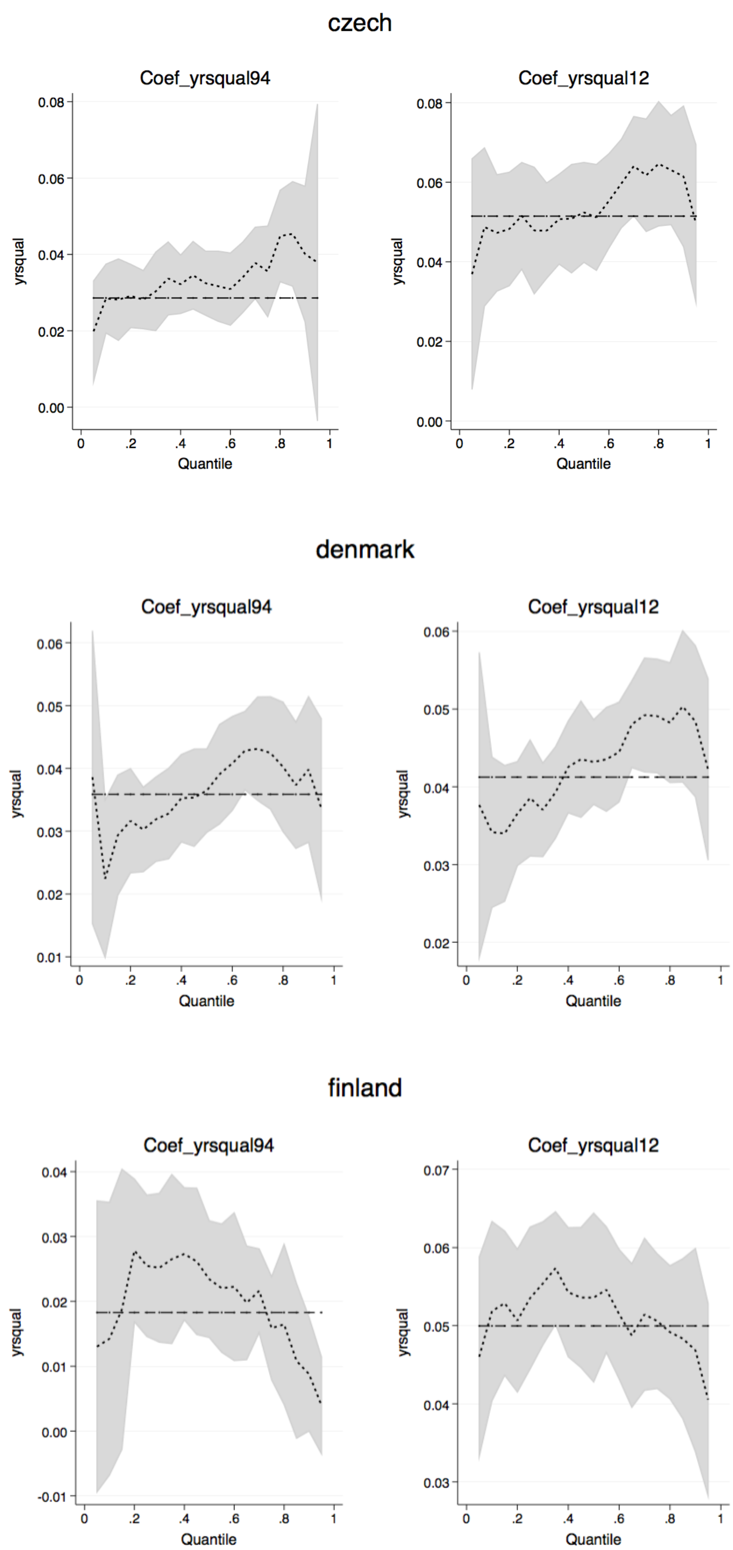


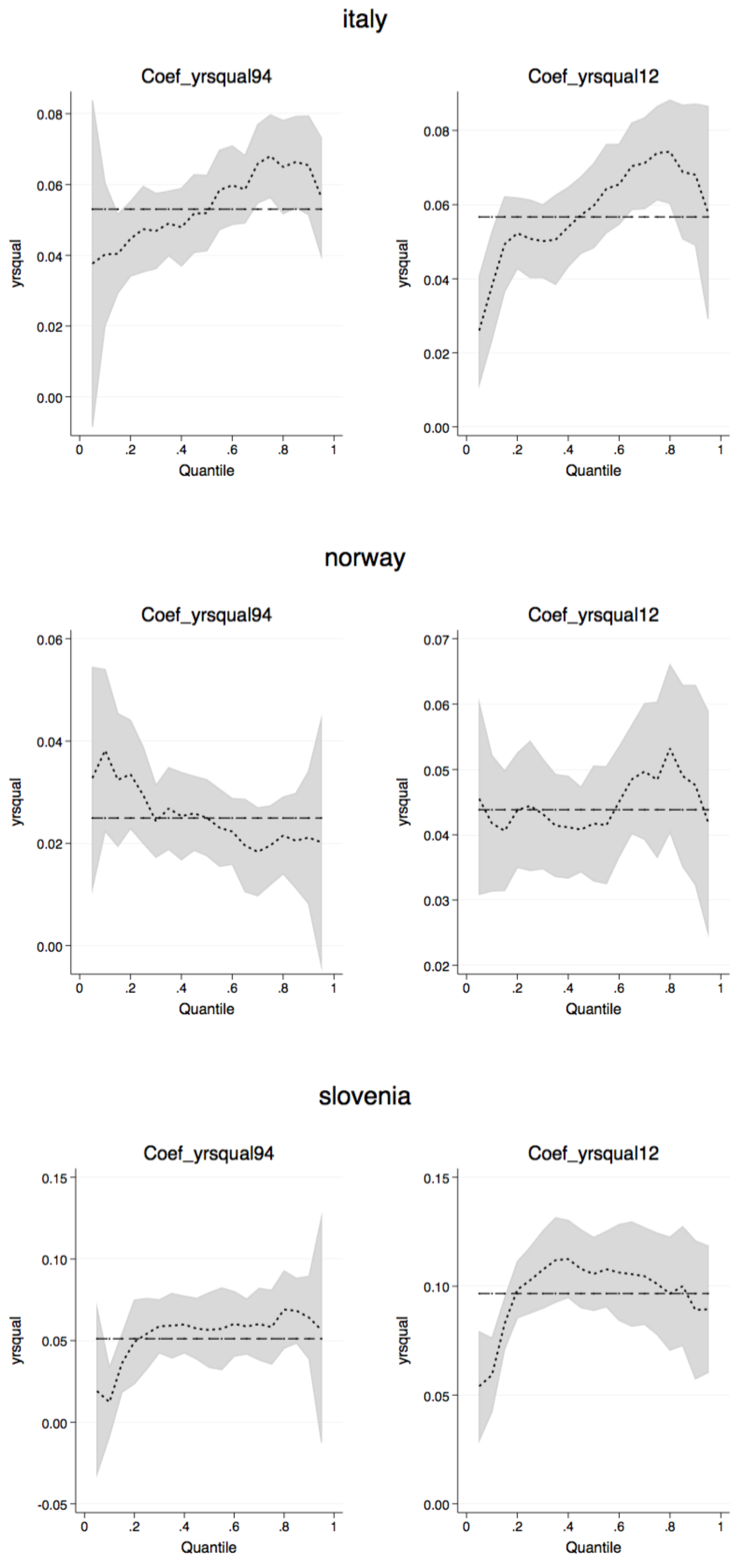




Note: For each country, the graphs show the coefficints of literacy from quantile regression in 1994 (left) and 2012 (right). X-axis represents quantiles and y-axis represents % change in wage in response to 1% change in literacy score. Horizontal line is the OLS coefficient. Shaded area is confidence interval.

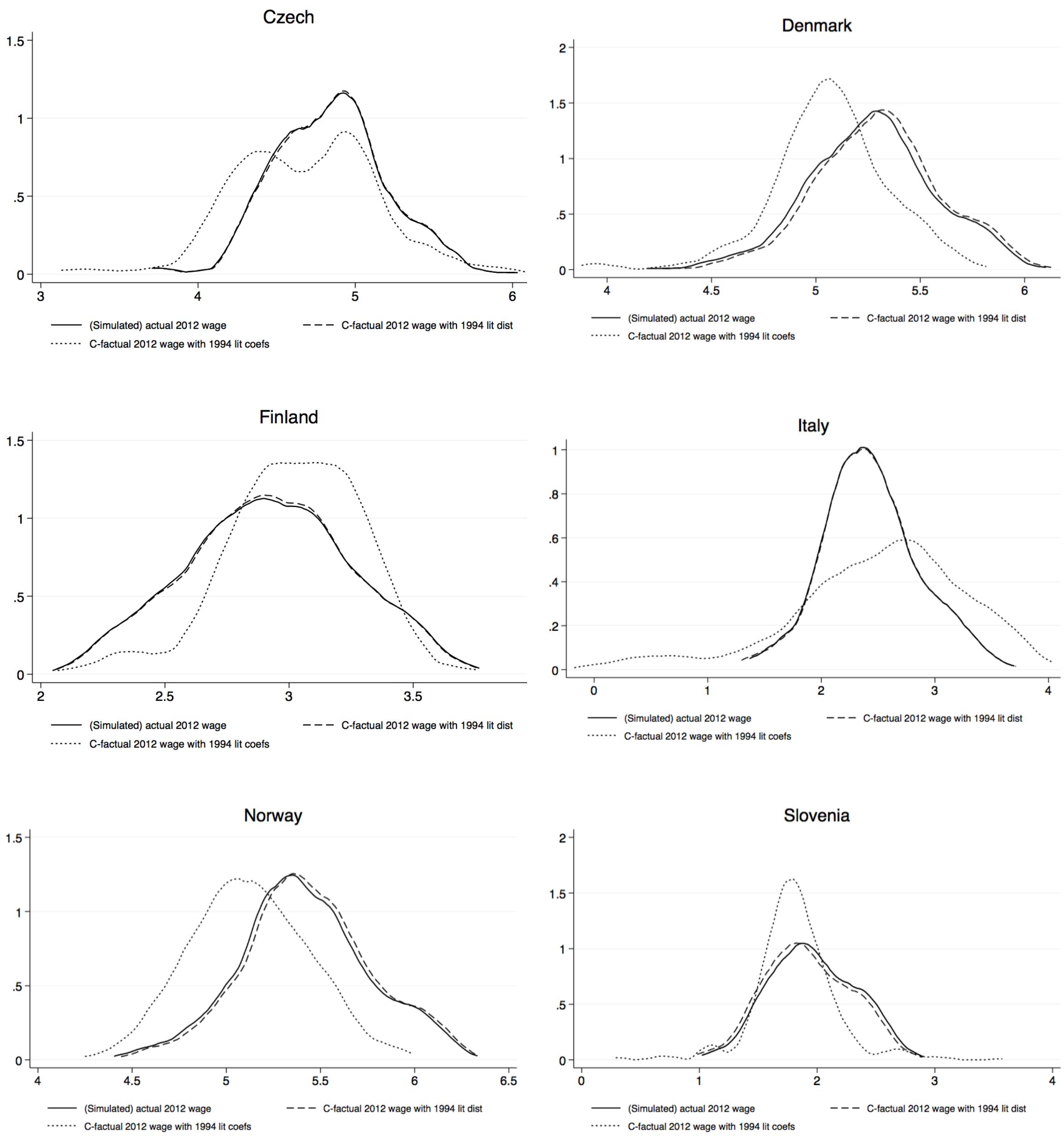
Figure 11: Quantile regression coefficients of education in 1994 and in 2012





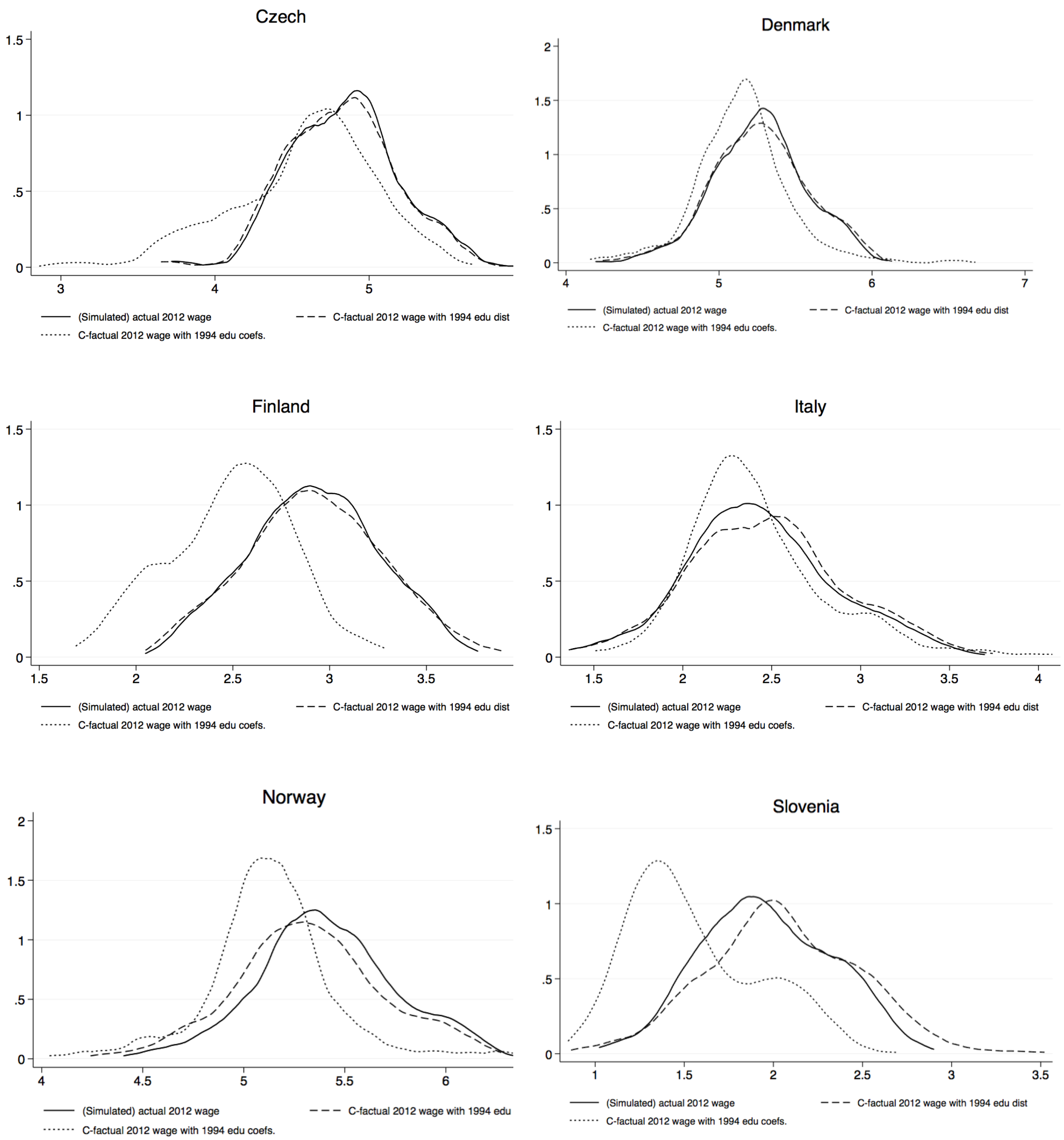
Note: Education version of Figure 11.

Figure 11: Simulated actual and counterfactual distributions (literacy)



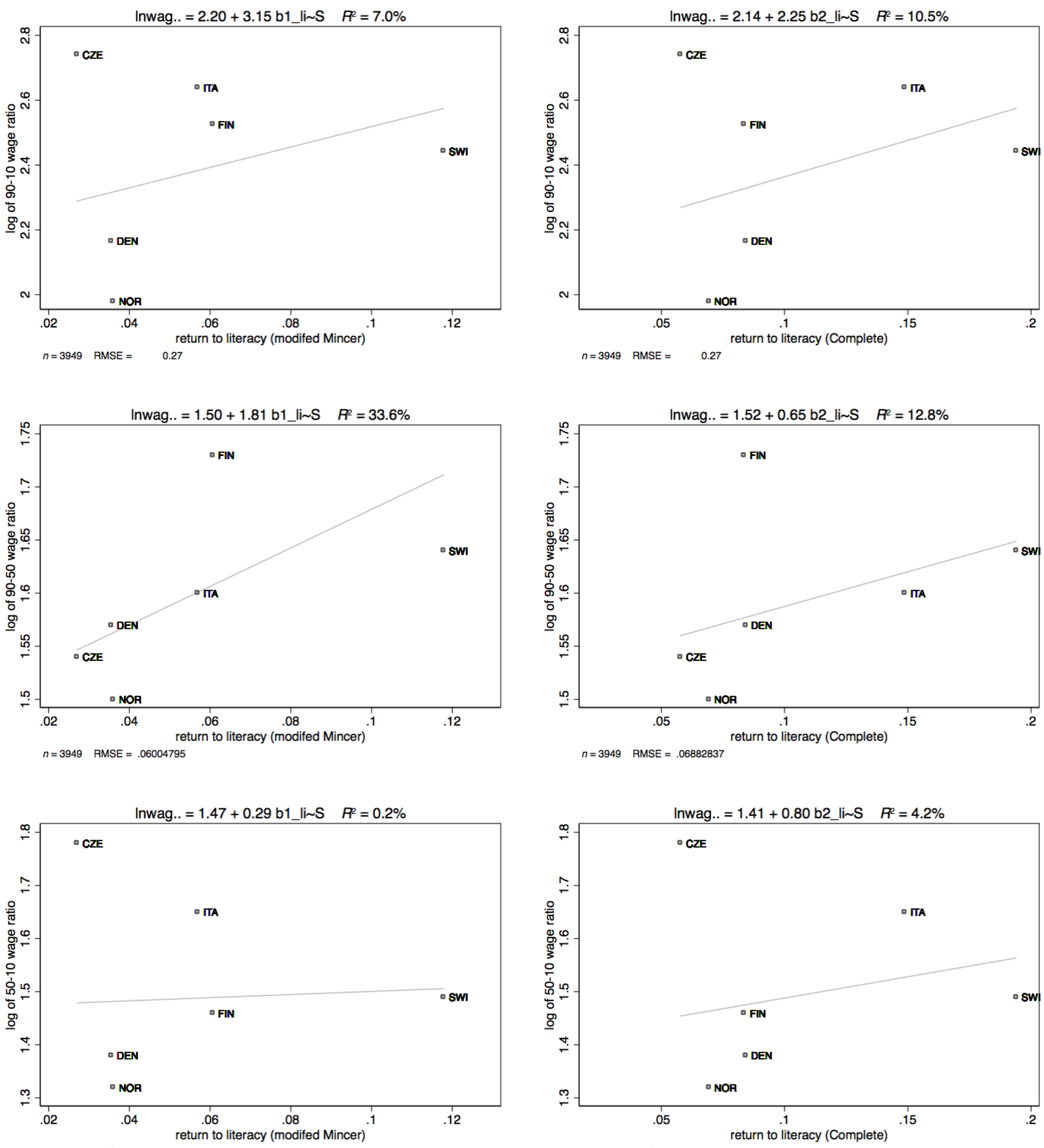
Note: Each box shows each country's simulated actual distributions of log wage in 2012 (a normal line), counter factual distributions of 2012 with 1994 literacy distributions (dashed line) and with 1994 literacy coefficients (dotted line). All are kernel density estimations.

Figure 11: Simulated actual and counterfactual distributions (education)



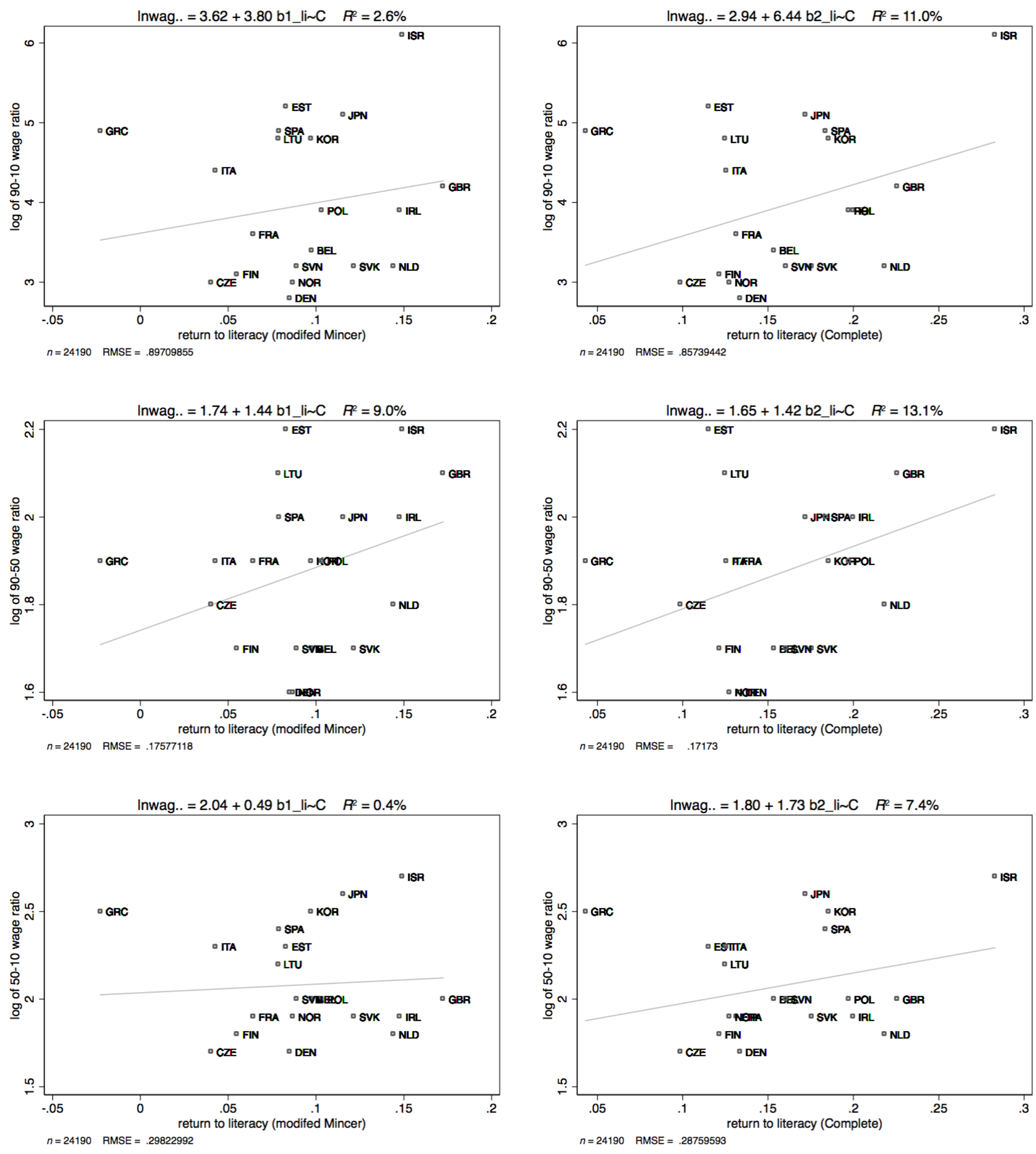
Note: Each box shows each country's simulated actual distributions of log wage in 2012 (a normal line), counter factual distributions of 2012 with 1994 education distributions (dashed line) and with 1994 education coefficients (dotted line). All are kernel density estimations.

Figure E.1: Return to IALS score and wage inequality in 1994 (OECD ver.)



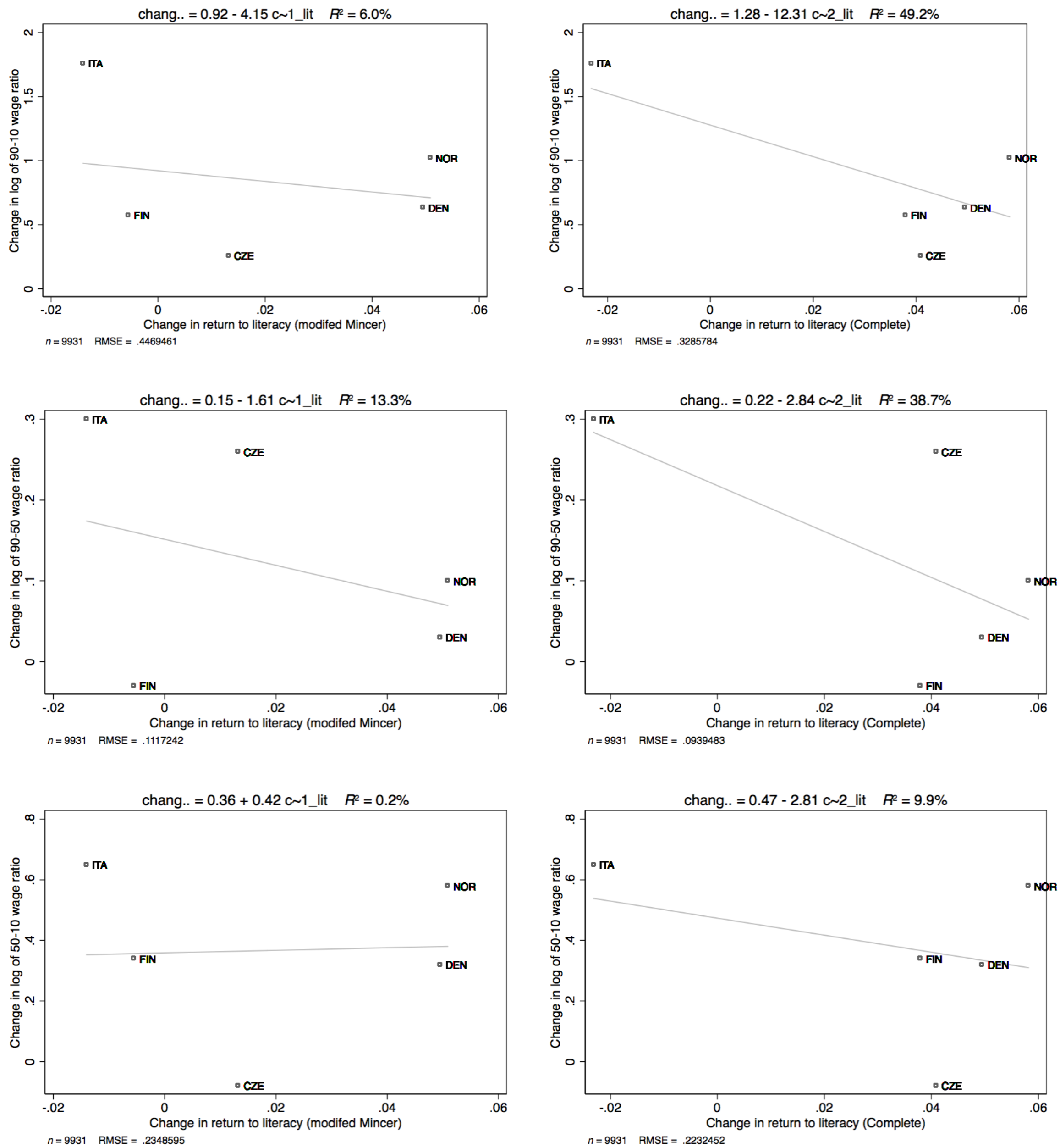
Note: Same figure as Figure 6 using the OECD data shown in Table 8.

Figure E.2: Return to PIAAC score and wage inequality in 2012 (OECD ver.)



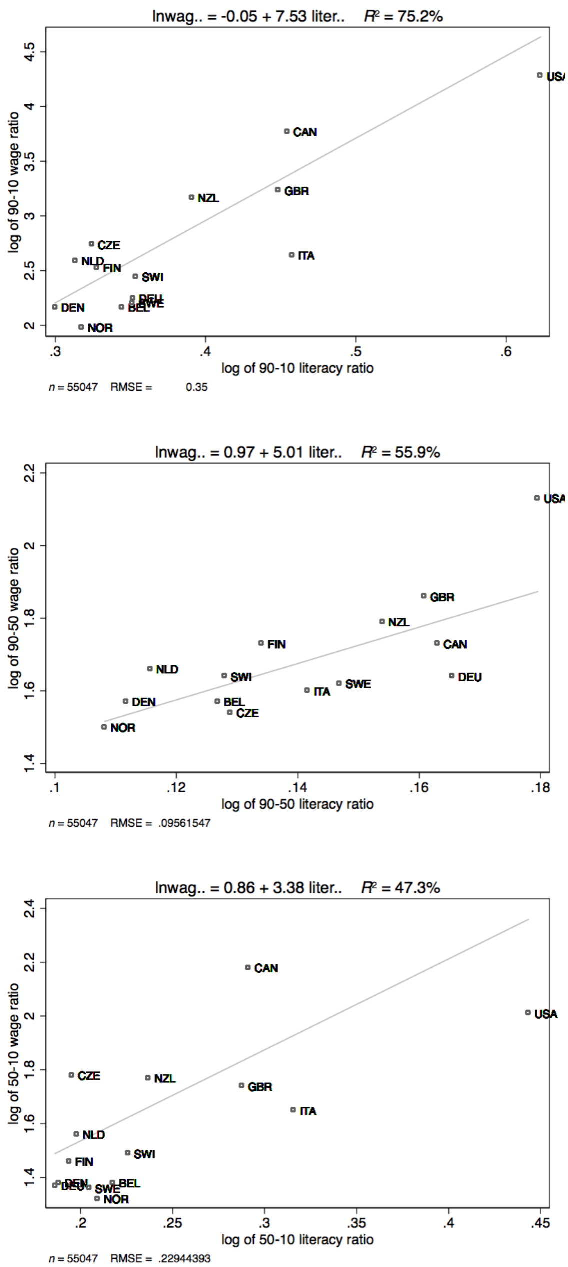
Note: 2012 version of the previous table.

Figure E.3: Change in return to literacy score and change in wage inequality (OECD ver.)



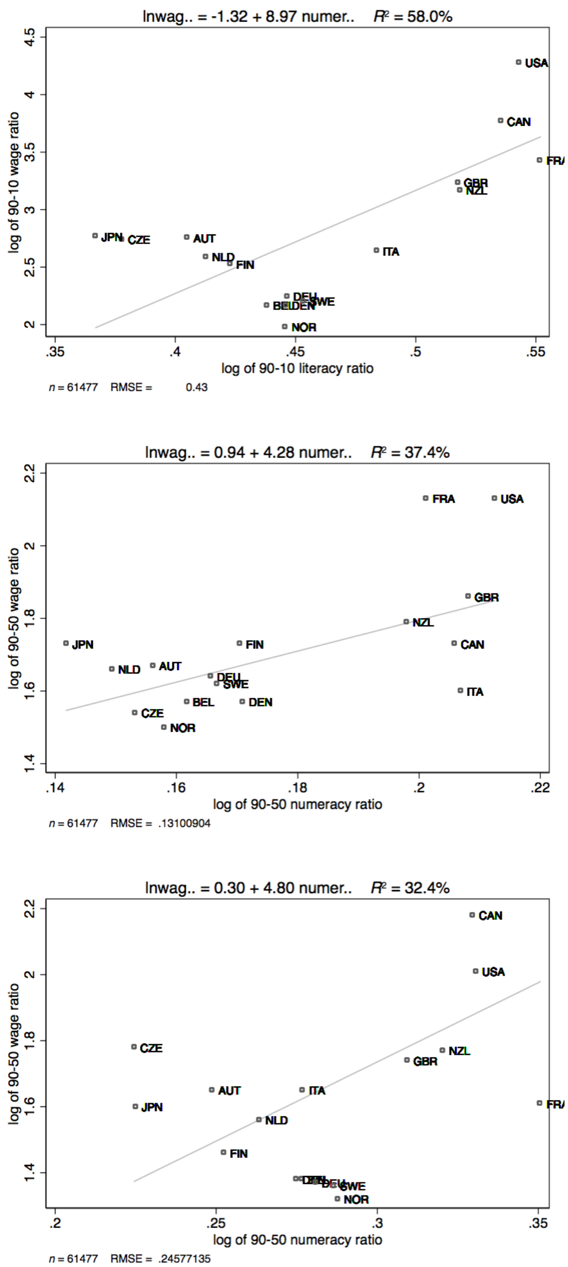
Note: OECD version of Figure 8

Figure E.4: Relationship between IALS score inequality and wage inequality in 1994 (OECD ver.)



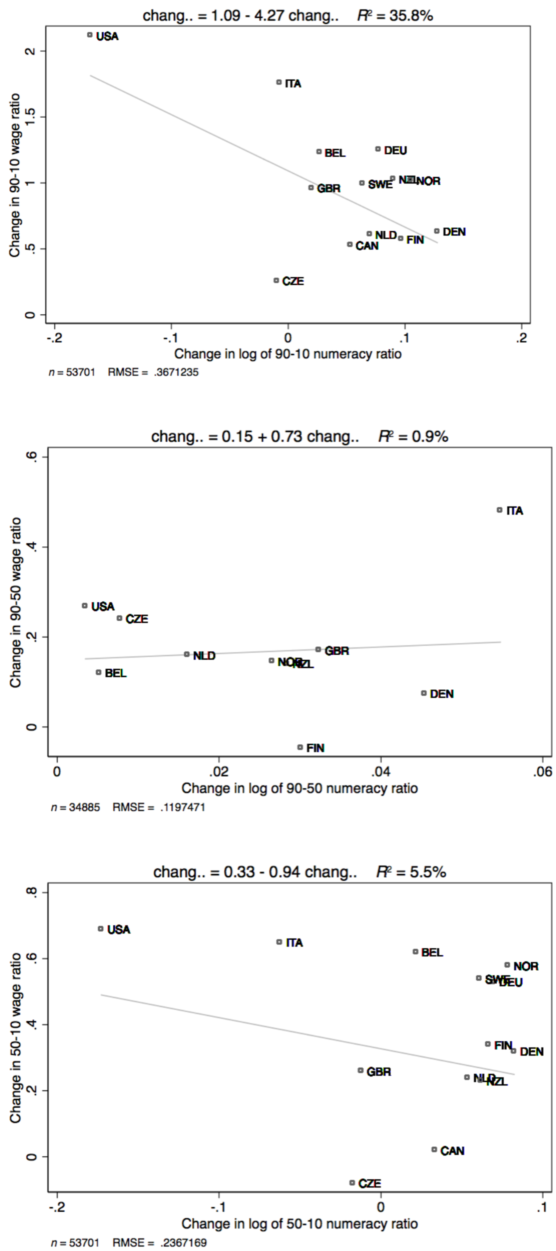
Note: A version of Figure 9 using OECD data presented in Table 8

Figure E.5: Relationship between PIAAC score inequality and wage inequality in 2012 (OECD ver.)



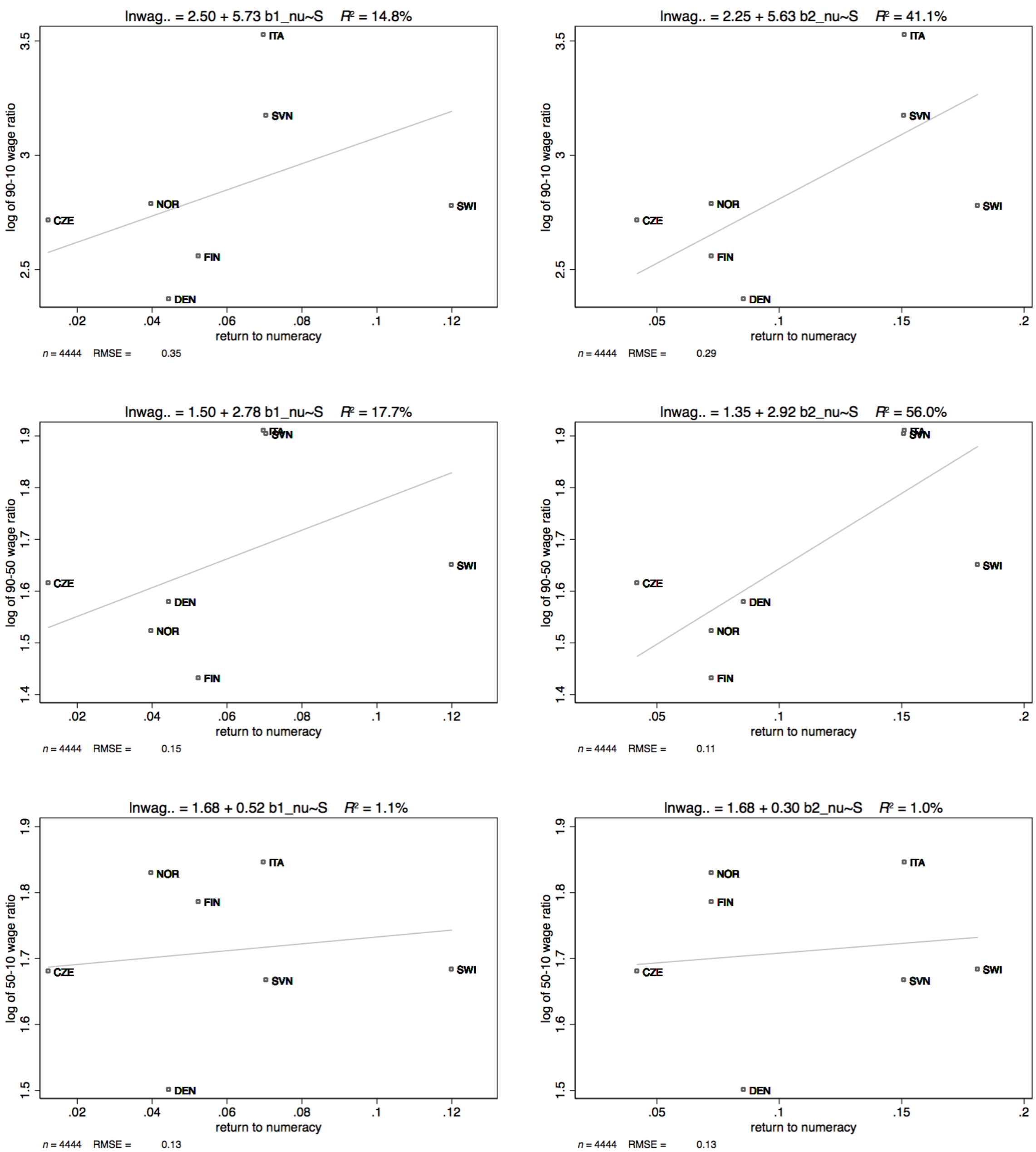
Note: A version of Figure 10 using OECD data presented in Table 8

Figure E.6: Relationship between change in inequality of test scores and change inequality of wages from 1994 to 2012 (OECD ver.)



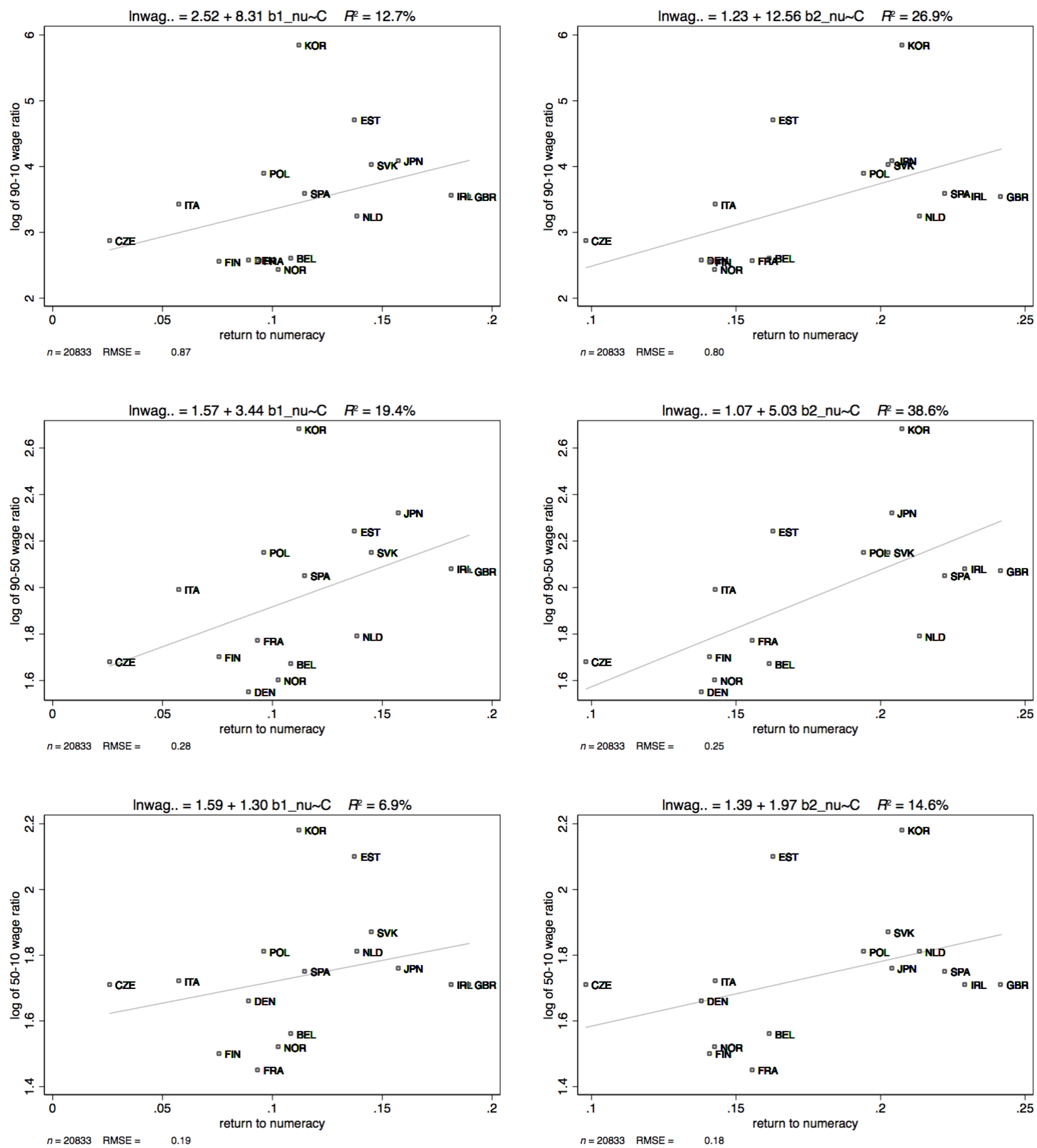
Note: A version of Figure 11 using OECD data presented in Table 8

Figure E.7: Return to IALS score and wage inequality in 1994 (numeracy ver.)



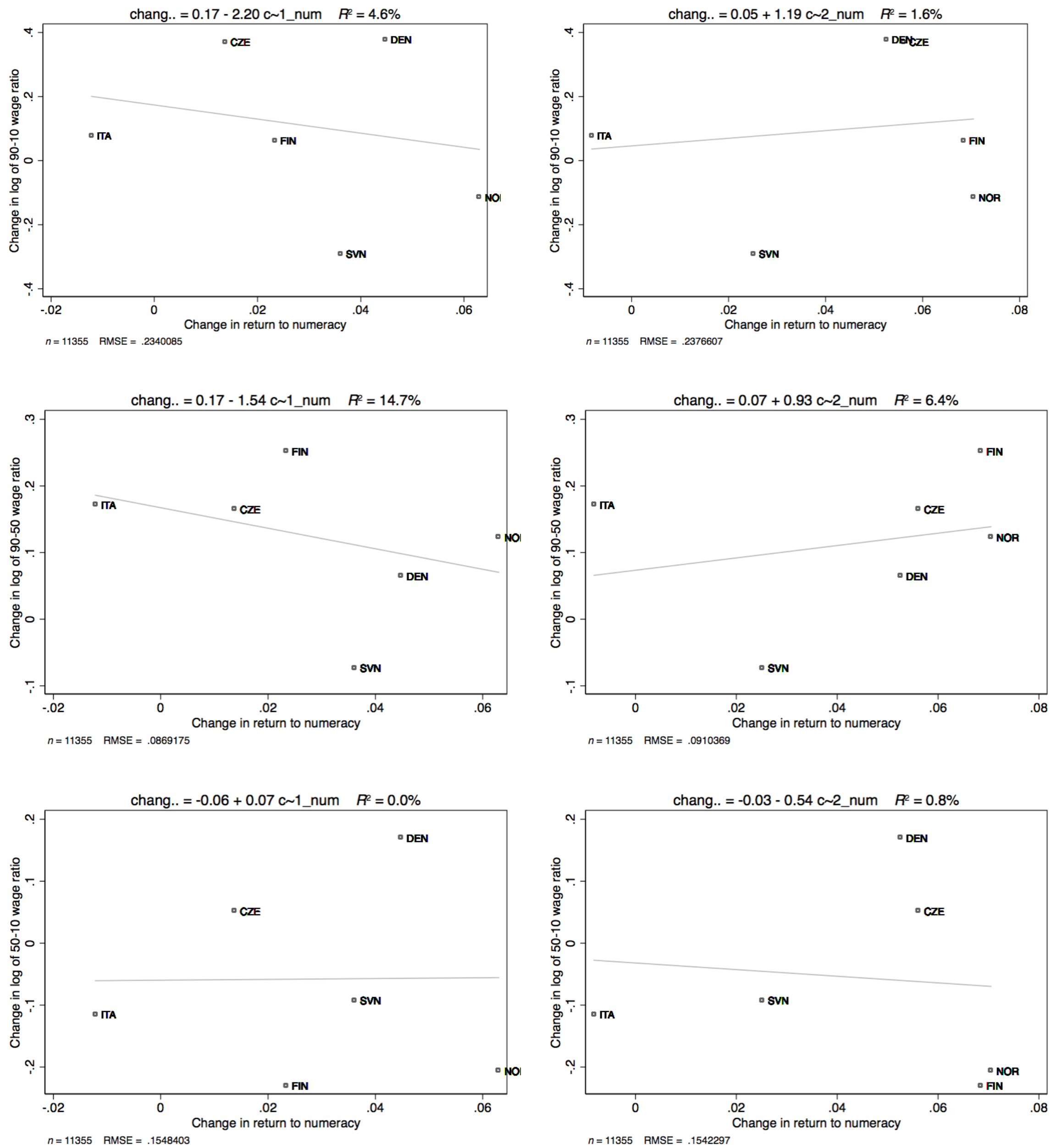
Note: Numeracy version of Figure 6.

Figure E.8: Return to PIAAC score and wage inequality in 2012 (numeracy ver.)



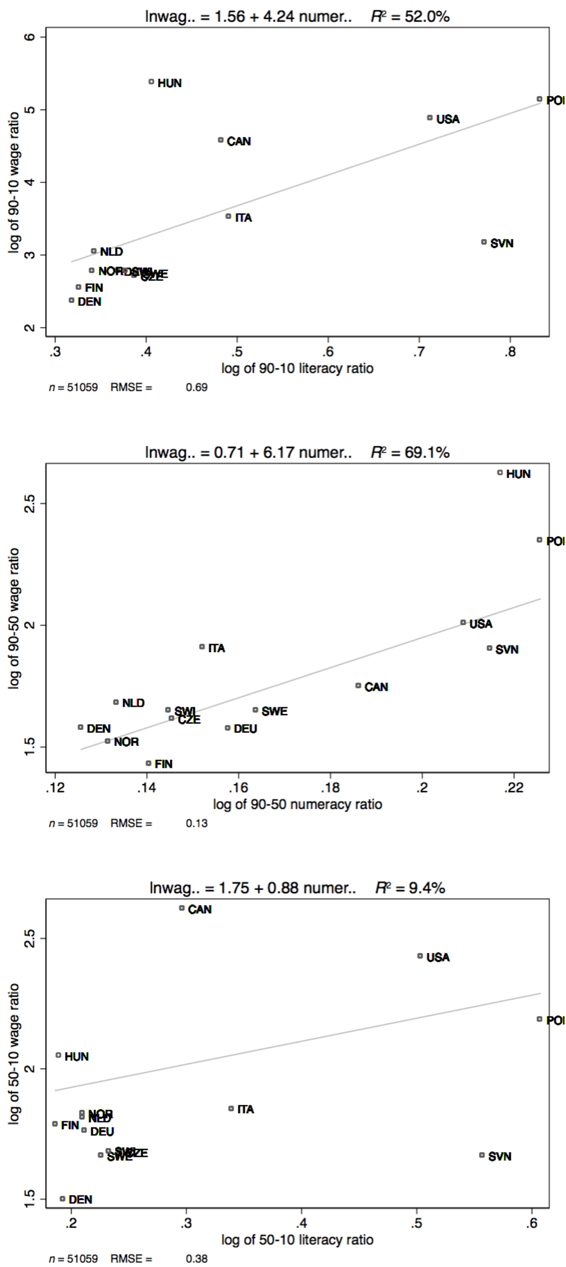
Note: Numeracy version of Figure 7.

Figure E.9: Change in return to PIAAC score and change in wage inequality (numeracy ver.)



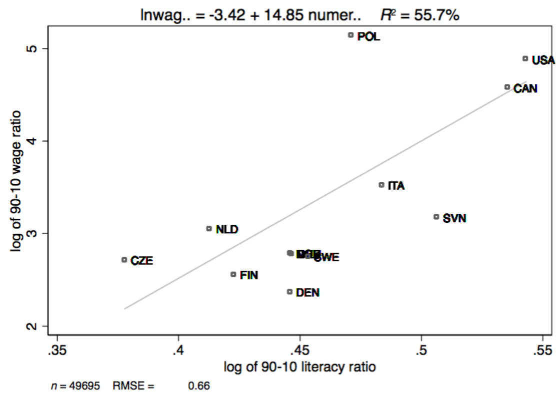
Note: Numeracy version of Figure 8

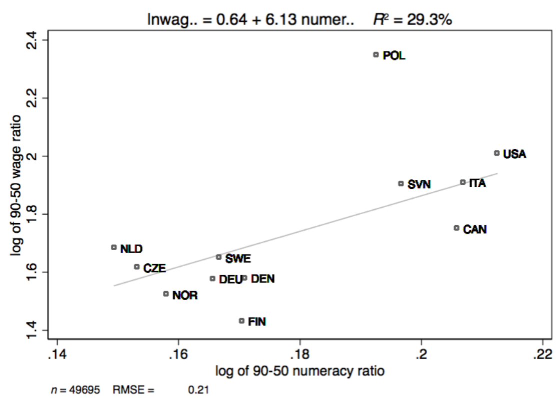
Figure E.10: Relationship between IALS score inequality and wage inequality in 1994 (numeracy ver.)

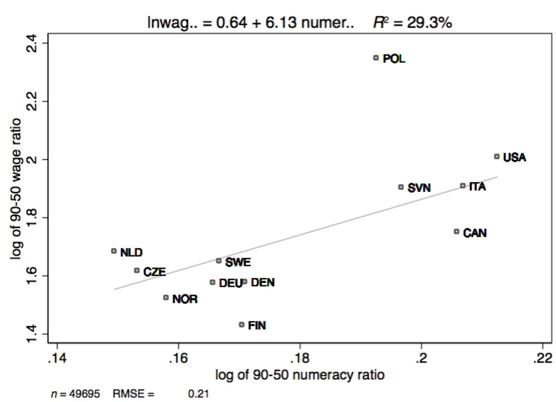


Note: Numeracy version of Figure 9

Figure E.11: Relationship between PIAAC score inequality and wage inequality in 2012

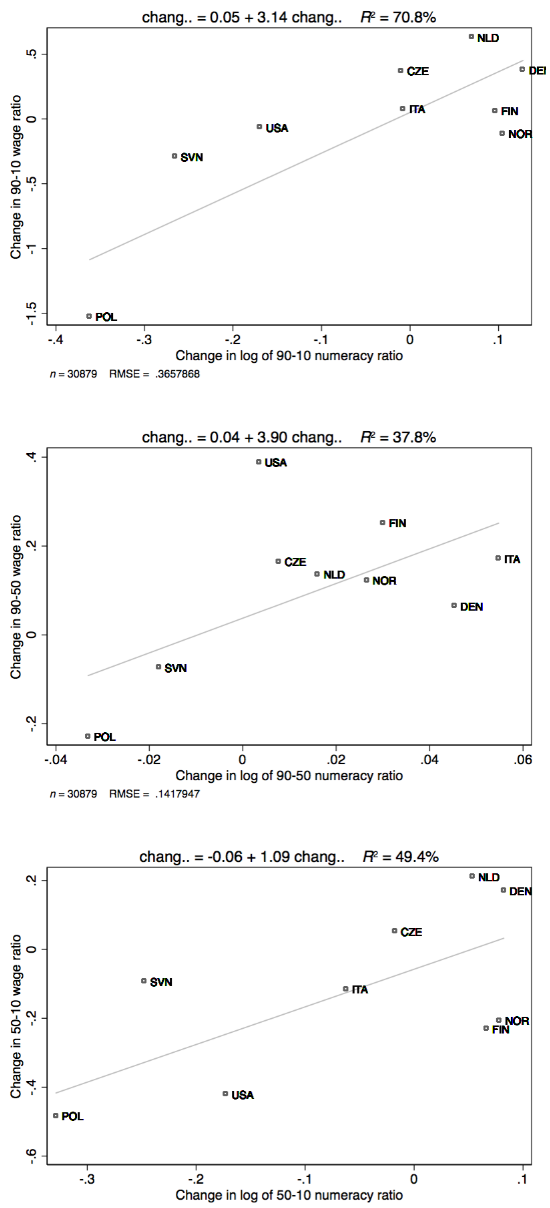






Note: Numeracy version of Figure 10

Figure E.12: Relationship between change in inequality of test scores and change inequality of wages (numeracy ver.)



Note: Numeracy version of Figure 11