Gender Differences in Skill Content of Jobs

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Abstract

More than half of the gender wage gap can be attributed to differences in wages within occupation. Using the PIAAC survey, we show that women perform less skill intensive tasks than men even within the same occupations. The gap in skill intensity cannot be explained by differential firm characteristics or differences in cognitive skills. Instead, we show that the skill intensity gap at the workplace is explained by the time spent in home production and the skill usage in leisure time. These empirical findings are consistent with a self-fulfilling equilibrium where statistical discrimination by firms causes gender differentials simultaneously in skill use both at the workplace and in leisure time activities at the same time.

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1 Introduction

The gender gap in labor market outcomes has been decreasing fast since World War II (Olivetti and Petrongolo, 2016). This positive trend is the result of the decreasing gender segregation across occupations and workplaces. More specifically, the relative position of women in education has increased and, as a consequence, women are now less likely to be segregated to work in occupations with low wages and low skill requirements (Reskin, 1993; Blau and Kahn, 2000). Even so, the pay gap has remained considerably large between women and men having very similar labor market characteristics: Cobb-Clark and Tan (2011) show that the current gender wage differences are much larger now *within* occupations than *between* occupations.

A small but growing strand of recent literature tries to uncover why women earn less than men in the the same occupation. The possible explanations are differences in bargaining power (Card et al., 2016), lower overtime hours done by women (Goldin, 2014), or differences in actual skill use. Black and Spitz-Oener (2010) use German survey data to show that women tend to carry out less skill-intensive tasks and consequently earn less than men even within the same "official" occupational category. The authors also argue that half of the gender wage convergence can be attributed to the convergence in executed tasks. Similarly, the convergence in skill use within occuptions has halved the part time wage penalty of women (Elsayed et al., 2017). The large within-occupation difference in skill use is surprising as occupations are characterized by a detailed list of tasks and duties as to what individuals should do at their workplace (ISCO, 2008).

This paper is the first which investigates directly the possible mechanisms which lead to lower cognitive skill use of women at the workplace. Our most important result is that neither job characteristics nor differences in cognitive test scores can explain the within occupational gender gap in cognitive skill use. Likewise, a wide set of demographic characteristics offer no explanation either. However, we find that activities outside the labor market such as housework and cognitive skill use in leisure time can explain both within and between occupational gender gaps in skill use. Our preferred explanation is a self-fulfilling equilibrium where statistical discrimination by firms causes gender differentials simultaneously in skill use at the workplace and in leisure time. More precisely, we argue that women are assigned less skill intensive tasks at the workplace because employers think that they are more willing to put in hard effort at home and as a consequence they are less able/willing to fulfill tasks with large skill and effort requirements than otherwise identical men. Finally, we investigate and rule out possible alternative mechanisms such as differences in preferences or discriminative assumptions about cognitive skills.

As a first step, we document that the tasks performed by women are significantly less skill intensive on average than those performed by men with the same abilities and in the same occupation. We use the international survey known as Programme for the International Assessment of Adult Competencies (PIAAC), which represents 16 countries. This data set is unique in the sense that it contains test scores measuring the ability of using cognitive skills as well as detailed information about the actual activities workers do at the workplace (e.g. how often they use a text editor, read directions or instructions, fill in forms etc.). The survey summarizes these activities into standardized indices measuring cognitive and non-cognitive skill use at work. We show that the gender gap in numeracy skill use is around 0.2 standard deviation and 0.1 standard deviation in literacy skill use and in using information and communication technology skills (ICT skills). Furthermore, the gender gap in skill use is apparent at every educational level and in every observed country. These differences are significant in economic terms as they correspond approximately to 4 years of schooling. The novelty of our research is that we control for the cognitive test scores of individuals to show that the gender differences in skill use cannot be explained by differences in the ability of using these skills. As we control for occupation (what women are supposed to do at the workplace) and for the ability of using cognitive skills (what women are able to do), the remaining gender gap itself may be interpreted as workplace discrimination.[1]

In the second part of the paper we show that: (i) differences in activities outside the labor market predict the gender gap in skill use; and (ii) this empirical fact can be explained by discriminative assumptions about the unobserved effort of workers. We match the time use survey of the International Social Survey Program to the PIAAC data based on demographic characteristics and show that women who are responsible for a disproportionately large share of housework or use their cognitive skill less in their leisure time end up doing less skill-intensive tasks at the workplace as well. In particular, the time spent on housework and the skill use in leisure time can fully explain the gender gap in skill use at work.

We argue that discrimination at the workplace can explain our empirical findings even if men and women have the same preferences toward skill use and housework. According to our preferred

[1] Jimeno et al. (2016) show that skill use at the workplace increases cognitive test scores. That is why the cognitive test scores over-control for discrimination if tasks are indeed allocated discriminatively.

interpretation, employers assume that women carry out a disproportionately large share of home production and as a consequence they are less willing or less able to exert high effort at the workplace (Albanesi and Olivetti, 2009). That is why employers assign easily monitorable and less skill-intensive tasks to women. Women observe the discrimination against them and translate their efforts from the workplace to home production. Finally, if skill use in leisure time and at the workplace are complements then discrimination at the workplace decreases skill use in leisure time even if we control for working hours and time spent on housework.

Although the empirical patterns are qualitatively consistent with the discriminative assumptions about the effort of workers, we further support our interpretation by ruling out some similar mechanisms as well. First and foremost importantly, we argue that the gender gap in skill use cannot be fully explained with differences in preferences. If women were to use skills less at the workplace and in their leisure time just because they have different skill use preferences toward skill use then we would expect that the gender gap in skill use in leisure time should be the same for the employed and for the unemployed[2]. As opposed to this, if men and women have similar preferences toward skill use but labor market discrimination temporarily alters the habit of using skills then we would expect larger gender differences in skill use in leisure time among the employed than the unemployed. In line with this, we show that employed women use their cognitive skills less in leisure time while there is no such difference among the unemployed. The second alternative mechanism is that women, whose jobs are lower paying and less skill intensive than the jobs of their spouses, may not be able to bargain for an equal division of housework. We can rule out this explanation as the relative wage and working hours within households cannot predict the skill use at work and the main results do not change when we consider single households. Third, we cannot find evidence that women are discriminated because employers underestimate their cognitive skills. In their corresponding analysis, Altonji and Pierret (2001) show that the initial decisions of employers are based on easily observable characteristics (e.g. gender), but as time goes on, employers learn the true skills of their workers. As a consequence, high ability workers with long experience tend to fulfill more skill intensive tasks and are less discriminated against based on gender than employees with shorter experience. Contrary to the prediction of the model, we do not find that the gender gap in skill use decreases with tenure. The final mechanism we investigate is whether

[2]Woman may be to to tired because of housework to exert high effort at the workplace. We also investigate this issue in Section 4.1.

employers assume that women at a certain age leave firms more likely for maternity leave, and that is why they assign less skill intensive tasks to these women (Yip and Wong, 2014). However, we find that age specific birthrates have only a minor effect on skill use at work.

Beyond the above cited literature, our paper also relates to the measurement of workplace tasks. The largest strand of literature uses official task descriptions of occupations to measure the activities performed at the workplace. These papers documented decreasing returns on routine tasks and increasing returns on non-routine cognitive tasks (Autor et al., 2003; Goos et al., 2009; Acemoglu and Autor, 2011; Autor and Dorn, 2013). Some recent papers apply self reported skill use measures (Spitz-Oener, 2006; Autor and Handel, 2013; Stinebrickner et al., 2017) and show large within occupational heterogeneity in cognitive skill use. We add to these papers by showing that women *systematically* use their cognitive skills less than men of the same occupation and cognitive skills.

The paper also relates to the effect of non-cognitive skills on labor market outcomes. Weinberger (2014); Deming (2017); Deming and Kahn (2018) show that the demand for non-cognitive skills increases over time. Furthermore, Cortes et al. (2018) argue that the increasing demand for social skills has positively affected the college premium of women. We add to this literature by showing that women report lower social skill use than men of the same occupation.

Our research has important policy relevance as well. We argue that policies aiming to affect the gender mix of occupations cannot eliminate the remaining gender gap: it is not enough to increase the number of women in high-salary, male dominated occupations, what should also be taken into account is how the tasks are distributed within occupations. Our results also suggest that activities at the workplace and in leisure time are closely interrelated and statistical discrimination might be an important channel which lead to within-occupation gender gap.

2 Data and descriptive statistics

We use the Programme for the International Assessment of Adult Competencies (PIAAC) survey for our analysis. The survey is unique as it measures not only the skill intensity of the tasks that the individual carries out during his or her work but also the cognitive skills of the respondents and the cognitive skill use in their leisure time. The survey assesses a broad range of abilities, from simple reading to complex problem-solving (Goodman et al., 2013). According to the OECD (2012) definition, the tests related to literacy are developed in a way so as to measure "understanding, evaluating, using and engaging with written text to participate in society, to achieve one's goals and to develop one's knowledge and potential" (OECD, 2012, p. 20). Similarly, the numeracy skill tests are aimed to measure "the ability to access, use, interpret, and communicate mathematical information and ideas, to engage in and manage mathematical demands of a range of situations in adult life" (OECD, 2012, p. 33). Hereafter we use these studies as the proxies of cognitive skills. The survey also provides information on the respondents' labor market status, education, social background, occupation, activities on the job etc. It also collects information on a wide set of leisure time activities (how often one reads journals in leisure time, whether one has a computer at home, how often the respondent uses a computer for communication in leisure time, etc). The answers on these categorical questions are summarized in four skill use indices (numeracy, reading, writing and ICT skill use). We standardized all indices to have a mean of zero and standard deviation of one.

Table 1. Definition of the Main Index Variables

Name of the index	Definition	
in the main analysis		
Numeracy	Index of use of numeracy skills at work (basic or advanced)	
Writing	Index of use of writing skills at work	Literacy at work*
Reading	Index of use of reading skills at work	Literacy at work*
ICT	Index of use of ICT** skills at work	
in the appendix		
Influence	Index of use of influencing skills at work	
Planning	Index of use of planning skills at work	
Ready to learn	Index of readiness to learn	
Task discretion	Index of use of task discretion at work	
Learning at work	Index of learning at work	

*The index of literacy at work combines the two indices, namely reading skills at work and writing skills at work, into one measurement by using the methodology developed by Anderson (2008).
**information and communication technologies

The skill use at work are measured by categorical questions indicating how often they do certain activities or use certain tools at their workplace. These detailed questions are summarized in 9 indices. In this analysis we focus on the summary indices of basic skills (numeracy skill at work, literacy skill at work and ICT skill at work) and examine whether there are any gender differences along these measures. Table 1 summarizes the short definition of the 9 indices, while Appendix Table 1 gives more detailed information about their construction. We will refer to the indices in the first panel of Table 1 as measures of skill intensity of the given job in our paper.

The study was conducted in 2011-2012 by interviewing about 5000 individuals (aged 16-65) in each of the participating countries. In our analysis we are focusing on 12 countries only, where we can link the PIAAC data to the time use information[3]. Altogether, we observe 36,798 working individuals (see Table 2) where 54% of the sample are women. Throughout the analysis we use the sampling weights provided by the OECD.

Table 2. Sample size by country and gender

Country	Men	Women	Total
Czech Republic	1,168	1,538	2,706
Denmark	2,016	1,960	3,976
France	1,634	1,811	3,445
Great-Britain	1,638	2,585	4,223
Germany	1,357	1,612	2,969
Japan	1,569	1,522	3,091
Korea	1,718	1,665	3,383
Norway	1,282	1,461	2,743
Poland	1,603	1,809	3,412
Russian Federation	466	1,173	1,639
Slovakia	1,155	1,420	2,575
Spain	1,254	1,382	2,636
Total	16,860	19,938	36,798

Table 3 provides basic descriptives for males and females. To facilitate comparison we also provide the estimated differences across gender and the t-statistics. We use sampling weights provided by the data set and we use the full sample (regardless of whether our main dependent variable

[3]In Section 3 we also investigate the gender gap by country.

- measure of skill intensity - is missing or not).[4] Male workers are somewhat more experienced and they are more likely to have full time jobs. Women tend to have higher levels of education and work at state owned companies and non-profit organizations. According to the literacy and numeracy test results, males are better in mathematics related problems while women have better literacy skills. These findings are similar to the patterns documented in the literature (Fryer and Levitt, 2010).

Table 3. Descriptive statistics of the main variables

Variable	Male	Female	Difference	t-stat
Experience (year)	19.94	17.73	-2.20	-7.37
	(0.21)	(0.20)		
Years of education	12.67	13.12	0.45	7.90
	(0.04)	(0.04)		
Share of full time workers	0.81	0.66	-0.14	-13.43
	(0.006)	(0.008)		
Share of those who have children	0.64	0.69	0.05	4.39
	(0.007)	(0.007)		
Native	0.81	0.82	0.01	0.66
	(0.007)	(0.007)		
Share of private organization	0.82	0.69	-0.13	-13.06
	(0.006)	(0.007)		
Share of public & non-profit organization	0.18	0.31	0.13	12.72
	(0.006)	(0.007)		
Average mathematic test score*	0.08	-0.09	-0.17	-7.47
	(0.015)	(0.020)		
Average literacy test score*	-0.02	0.03	0.05	2.14
	(0.017)	(0.021)		
Observations	19,313	17,319		

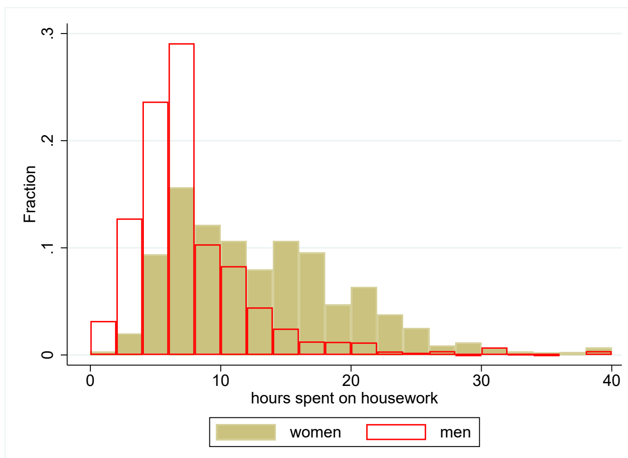
*Standardized test score with a mean of 0 and a variance of 1

The information on housework comes from the fourth wave of the International Social Survey Programme: Family and Changing Gender Roles (ISSP). The aim of the survey is to measure attitudes toward marriage, child bearing and activities pursuede in leisure time and at the workplace

[4] The results are visually the same for the sub-sample where all measures of the skill intensity of job is available.

(ISSP, 2016). The database contains self-reported information on the hours spent on housework. As a first step, we calculate the average housework by country of origin, gender, marital status, 1 digit occupational category, educational level and by the number of children. These categorical variables define 1120 distinct segments and we merge the segment level average hours spent on housework to the individual observations in the PIAAC data. The distribution of weekly housework is shown in Figure 1. According to the figure, the hours spent on housework vary significantly across individuals and we also find important gender differences in this regard. On average, women devote on average 5.5 more hours to housework than men and they are significantly less likely to report fewer than 10 hours.

Figure 1. Distribution of weekly housework by gender (hours)



Notes: The number of hours spent on housework is winsorized at 40 hours.

We can also test the reliability of the results by comparing the self reported and spouse reported hours spent on housework. The ISSP surveys only one member of the household and the respondent has to gauge the amount of her own and her spouse's housework. If people systematically overestimate their own housework then we would assume that the self reported housework is larger than the spouse reported housework.[5] In contrast, Appendix Figure 1 highlights that the distribution of housework remarkably overlaps for both men and women. That is why we conclude

[5]This may be especially problematic among women, who may over-report their housework because of social expectations.

that the number of self reported hours spent on housework is indeed a precise measure of the activities at home.

Finally we plot the distribution of hours spent on family care. One may argue that people responsible for an especially large amount of housework can devolve family care to other adults in the family/household. We investigate the issue in Appendix Figure 2. First, Panel A shows that women spend more time not only on housework but also on family care. Second, Panel B groups the people into 20 equally sized bins by the amount of reported housework and plots the average hours spent on family care for men and women. The figure highlights that women spend more time on family care at every level of housework and people who report larger amounts of housework also spend more time on family care. Based on these facts, we conclude that there is no trade off between doing more housework and spending more time on family care.

3 Results

This section shows that women use their cognitive skills at the workplace less often than men but the heterogeneity in job characteristics and individual skills cannot, in itself, explain this gender gap. To prove this claim, we run OLS regressions where the left hand side variable is one of the indices measuring the skill intensity of the job (see Table 1). We pool all countries in our sample together. Our main right hand side variable is gender, while controlling for different sets of variables:

$$y_i = \alpha + \beta * female_i + X_i \gamma + u_i \tag{1}$$

where y_i denotes the examined skill intensity measure (standardized to have a mean of zero and a standard deviation of one), X_i is the set of control variables. The main coefficient of interest is β showing the gender gap in skill use at the workplace. Most importantly we can make use of the data on numeracy and literacy test scores of the survey respondents.[6] The test scores enable us to show that women do not use their cognitive skills less because of their lack of skills. Besides individual skills we also mimic a Mincerian-type wage equation and control for years of

[6]The survey does not measure ICT skills.

education, experience, experience-square, occupation (3 digit ISCO codes), etc.[7] As occupations are defined by a detailed list of tasks and duties the employees have to fulfill at their workplace, the occupation categories alone should explain the individual heterogeneity in skill use at work. By including occupational categories and cognitive test scores into the control variables, we do not only control for task what employees should carry out at work but also for the individual's ability of using cognitive skills.

The point estimates for equation 1 are shown in Table 4. The three skill use indices are shown in separate panels while the columns differ in control variables. According to Column (1), women use their cognitive skills with an approximately 0.3 standard deviation less than males. The raw differences are somewhat larger in numeracy skill and literacy skill use (coef. 0.32, s.e. 0.02) than in ICT skill use (coef. 0.27, s.e. 0.02).

To better understand the magnitude of these point estimates we add years of education and cognitive test scores to Column (2). Not surprisingly, the years of education is positively correlated with skill use at work. On the one hand, workers with one more year of education use their cognitive skills with 0.05-0.1 standard deviation (s.e. 0.005) more. This means that the gender gap in cognitive skill use is large: it is of the same magnitude as approximately 3-4 extra years of schooling.

Turning to the effect of cognitive test scores, they cannot explain the gender gap in skill use either and they have only a limited effect on the reported skill use at work. While we do not find significant relationship between cognitive test scores and the use of literacy and ICT skills, the cognitive test scores have a large effect on numeracy skill use. Workers with one standard deviation larger numeracy test scores use their numeracy skills with 0.15 standard deviation more (s.e. 0.03) but better literacy skill scores do not effect significantly their numeracy skill use.

[7]The remaining control variables are country fixed effects, parents' highest level of education and parents' immigration status, dummy for full time work, self-employment dummy, dummy for those having a permanent contract, dummies for 1 digit industry, 5 firm size categories, private sector control and a set of social skills (categorical variable for cultural engagement, political efficacy, social trust, social trust 2 and health status).

Table 4. Gender gap in skill use at work

	(1)		(2)		(3)	
Panel A: Numeracy skill use at work						
	coeff.	(s.e.)	coeff.	(s.e.)	coeff.	(s.e.)
Gender Gap	-0.293***	(0.017)	-0.229***	(0.017)	-0.144***	(0.016)
Years of education			0.054***	(0.003)	0.027***	(0.004)
Literacy test scores			-0.040	(0.030)	-0.006	(0.023)
Numeracy test scores			0.198***	(0.030)	0.143***	(0.022)
Panel A: Literacy skill use at work						
Gender Gap	-0.298***	(0.016)	-0.254***	(0.017)	-0.172***	(0.017)
Years of education			0.103***	(0.004)	0.049***	(0.004)
Literacy test scores			0.045**	(0.022)	0.007	(0.019)
Numeracy test scores			0.065***	(0.024)	0.014	(0.019)
Panel C: ICT skill use at work						
Gender Gap	-0.275***	(0.017)	-0.245***	(0.018)	-0.134***	(0.018)
Years of education			0.072***	(0.004)	0.037***	(0.004)
Literacy test scores			0.053**	(0.022)	0.038*	(0.023)
Numeracy test scores			0.050**	(0.025)	0.004	(0.024)
Controls for job characteristics	No		No		Yes	

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Control variables differ by column. Column (2) controls for years of education and standardized literacy and numeracy skills. Column (3) also controls for partner dummy, child dummy, years of education, experience, experience^2, occupation categories (ISCO 3 digit), country fixed effects, parents' highest level of education and parents' immigration status, dummy for full time work, self-employment dummy, dummy for having a permanent contract, dummies for 1 digit industry, 5 firm size categories, private sector and a set of social skills (categorical variable for cultural engagement, political efficacy, social trust, social trust 2 and health status). Standard errors are calculated with the jackknife method (suggested by OECD, 2013) using 80 replication weights. All of the the results are calculated by using sampling weights provided by the survey.

Column (3) incorporates the full set of individual and job characteristics. The control variables are experience, square of experience, dummies for one digit industry codes, 5 firm size categories and a wide set of information on family background and non-cognitive social skills. Most importantly, Column (3) includes 3-digit ISCO codes to control for tasks the workers should execute at their workplace. According to the results, these variables cannot explain the gender gap in skill use: two-thirds of the raw gender gap in numeracy and literacy skill use and half of the raw ICT skill use remain unexplained.

Heterogeneity of gender gap by groups. We also investigate whether the gender gap in skill use differs by groups. First, we estimate the skill use by country. Appendix Table 2 shows that there is a significant heterogeneity across countries. We observe the largest gender gap in skill use in Korea and Japan, where gender inequality is traditionally large. Surprisingly, the gender gap in skill use is also very large in Scandinavian countries (Denmark and Norway), which are considered some of the most gender-equal societies. In contrast, we find the smallest gender gap in skill use at work in the Post-Communist countries (Poland, Russia, Slovakia). These countries have the lowest gender gap in numeracy and literacy skill use but above average gender gap in ICT skill use.

Appendix Figure 3 plots the gender gap in skill use by educational categories. We find a significant gender gap in every educational category. Women with secondary education find the largest penalty in numeracy and literacy skill use compared to men of the same educational level. This difference remains significant even if we control for occupation, cognitive test scores and other control variables. Furthermore, women with professional degrees suffer the largest penalty in ICT skill use but the gap decreases once we control for worker composition.

We do not find large heterogeneity across broad occupational categories either. Appendix Figure 4 shows that the gender gap has similar magnitude in every broad occupational categories [8]. The only notable exemptions are the service jobs where the gender gap in literacy and ICT skill use is above average although do not find such a difference in numeracy skill use.

Gender differences in cognitive skills and skill requirement of jobs. The cognitive test scores of men and women do not differ much on the average (Table 3) and the cognitive test scores only have a small effect on the actual skill use at work (Table 4). Still, we can construct a simple theoretical scenario where the gender gap in skill use at work is driven by differences in cognitive skills. Assume that women have better cognitive test scores than men in occupations with very low skill requirements (thus without gender gap in actual skill use) while women have relatively lower cognitive test scores in occupations with high cognitive skill requirements (thus large gender gap in actual skill use). In this case the cognitive test scores and the gender gap in skill use would be uncorrelated in the whole sample but negatively correlated across occupations. To test this scenario, Appendix Figure 5 plots the average skill use at work by the gender gap in skill use. Every dot displays a specific 3-digit ISCO code. The horizontal axis shows the average gender gap in cognitive test scores in a given occupation (a positive number means that women in that occupation have better skills than men on average). The vertical axis represents the average skill

[8] The categories are based on 1 digit ISCO codes.

use in the given occupation[9]. The figure highlights that women have higher cognitive test scores than men in occupations with high literacy skill use but the gender gap in cognitive test scores are uncorrelated with numeracy and ICT skill use. Based on these facts, we conclude that the gender gap in skill use cannot be explained by the lack of cognitive skills in highly skill-intensive occupations.

3.1 The gender gap in skill use and activities outside the labor market

In the previous section we showed that the gender gap in skill use cannot be explained by demographic composition, occupation, firm characteristics, or by the differences in ability. In this section we argue that the number of working hours and activities outside the labor market can explain the gender gap in skill use at work. To prove this claim we show that the gender gap in skill use vanishes once we control for working hours, hours spent on housework and skill use in leisure time. In particular, we re-estimate Equation 1 conditional on these variables. The estimation results can be found in Table 5. Each panel shows the results of a specific skill use measure. (numeracy, literacy or ICT skill use at work) while the columns differ in control variables. Similarly to our previous results, the starting point is the unconditional gender gap (Columns 1-3).

As a first step, we augment our analysis by controlling for the number of working hours because as Goldin (2014) pointed out, the gender gap in wages crucially depends on overtime hours. According to Column (1), the gender gap in skill use at work decreases to 0.2 standard deviation once we control for working hours and the point estimates are very close to each other at every skill use measure. In particular, one third of the raw gender gap in skill use can be explained by differences in working hours[10]. The first difference among the skill use indices arises as we control for differences in hours spent on housework. Column (2) shows that the gender gap in numeracy and ICT skill use at the workplace decreases with 0.1 standard deviation once we control for the hours spent on housework. The most striking result is that the gender gap in literacy skill use fully disappears once we include the hours spent on housework: the point estimate is close to zero and statistically insignificant (-0.03 s.e 0.02) Finally, we control for the use of cognitive skills in leisure time (Column (3)). The results show that the gender differences in skill use in this area

[9] For the sake of simplicity, we pool the skill use of men and women together.

[10] Table 4 Column (1) shows that the unconditonal gap is 0.3 standard deviation.

can predict the gender differences in skill use at work. The number of working hours, the amount of housework and the skill use in the leisure time can explain the whole gap in literacy and ICT skill use and two-thirds of the gender gap in numeracy skill use.

Table 5. Skill intensity of the job and activities in leisure time

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Numeracy skill use at work						
Gender gap	-0.209***	-0.138***	-0.078***	-0.103***	-0.075***	-0.007
	(0.019)	(0.021)	(0.020)	(0.016)	(0.022)	(0.021)
Panel B: Literacy skill use at work						
Gender gap	-0.193***	-0.031	0.006	-0.122***	-0.084***	0.005
	(0.018)	(0.022)	(0.017)	(0.018)	(0.022)	(0.018)
Panel C: ICT skill use at work						
Gender gap	-0.199***	-0.108***	-0.016	-0.096***	-0.040**	0.061***
	(0.017)	(0.019)	(0.018)	(0.018)	(0.019)	(0.016)
Working hours	YES	YES	YES	YES	YES	YES
Housework		YES	YES		YES	YES
Skill use in leisure time			YES			YES
Additional controls				YES	YES	YES

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Control variables differ by column. The main control variables are the working hours, hours spent on housework and the standardized indices measuring skill use in leisure time. The additional control variables are the same as in Table 4 Column (3): partner dummy, child dummy, years of education, experience, experience^2, cognitive test results, occupation categories (ISCO 3 digit), country fixed effects, parents' highest level of education and parents' immigration status, dummy for full time work, self-employment dummy, dummy for having a permanent contract, dummies for 1 digit industry, 5 firm size categories, private sector and a set of social skills (categorical variable for cultural engagement, political efficacy, social trust, social trust 2 and health status). Standard errors are calculated with the jackknife method (suggested by OECD, 2013) using 80 replication weights. All of the the results are calculated by using sampling weights provided by the survey.

To show that the activities in leisure time are not only a proxy of job characteristics, we re-estimate Columns (1)-(3) with the inclusion of a wide set of control variables on occupation, worker and job characteristics (Columns (4)-(6)). The most important result is that working hours and activities outside the workplace affect the skill use at work conditional on occupation and cognitive abilities as well. According to Column (6), if we introduce every control variable, the gender gap in literacy skill and in numeracy skill use disappears. What is more, conditional on job characteristics and activities in leisure time, women use their ICT skills more at the workplace than men. Finally, the coefficients of skill use in leisure time and the hours spent on housework remain similar if we control for occupation and cognitive ability (Appendix Table 3). Based on these empirical facts, we conclude that the activities in leisure time are not merely a proxy of job characteristics or the abilities of employees[11].

One possible threat to our identification strategy is that some people may report working from home as skill use in leisure time. However, the survey explicitly asks for the skill use *which is not related to paid work*. Moreover, we re-estimate Table 5 using only blue collar workers[12] as the tasks done in these occupations are much harder to execute from home. As Appendix Table 4 shows, the point estimates remain almost the same.

To provide further evidence suggesting that skill use in leisure time does not only proxy skill use at work, we present the gender gap in skill use at work as a function of skill use in leisure time. If the self reported skill use in leisure time only mirrors the amount of working from home then we would expect a lower gender gap in skill use at work among workers who do not use their skills in leisure time. As opposed to this, the gender gap in skill use at work is similar at every level of skill use in leisure time. To demonstrate this, we order individuals by skill use in leisure time and group them into twenty equally sized bins. Second, we compute the unconditional and conditional gender gap in skill use at work in every bin. Figure 2 summarizes the results separately by skill use indices. The horizontal axis shows the average of skill use in leisure time in every bin while the vertical axis shows the gender gap in skill use at work. All indices are standardized to have a mean of zero and a standard deviation of one.

In the case of the figures on the left, our starting point is always the unconditional differences and we introduce our two main control variables - working hours and housework - step by step to the figure. The starting point for the figures on the right is always the conditional differences. According to the figures, women use their skills at their workplace by 0.2 standard deviations less often than men conditional on skill use in leisure time. This result is similar at every level of skill use in leisure time and in every skill use index. Figure 2 highlights that the gender gap in skill use decreaseses significantly once we control for working hours.

Finally we add the hours spent on housework to the control variables. As a consequence, the gender gap in skill use at work further decreases in every skill measure. Moreover, the gender gap

[11]If women were to use less skills in leisure time and at the workplace because of lack of cognitive skills, then we would expect that the coefficient of skill use in leisure time turns to be zero once we control for cognitive skills.

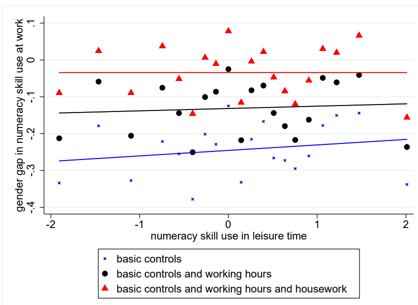
[12]We define occupations as blue collar if its ISCO code starts with 5 or a larger number.

diminishes in literacy and ICT skill use once we control for working hours and activities made in leisure time.

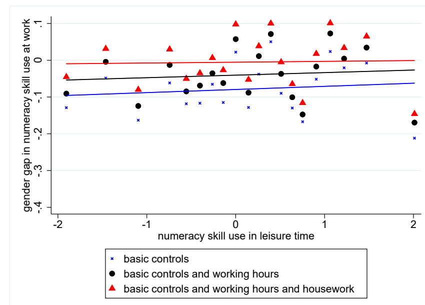
Figure 2. Gender gap in skill use by skill use in leisure time

Panel A: numeracy skill use

The unconditional gap

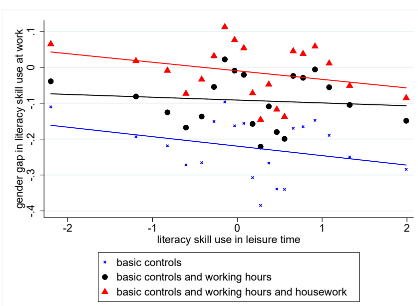


The conditional gender gap

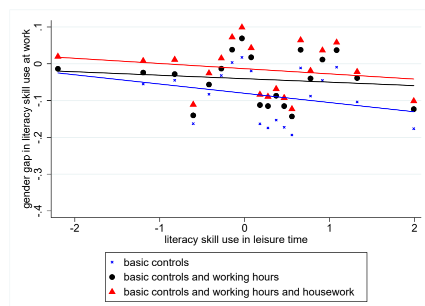


Panel B: literacy skill used at work by education level

The unconditional gap

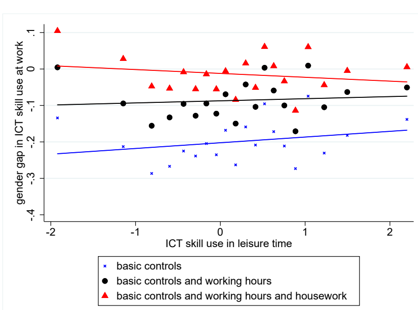


The conditional gender gap

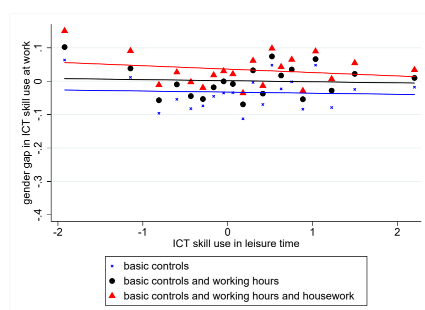


Panel C: ICT skill used at work by education level

The unconditional gap



The conditional gender gap



4 Discussion

The previous section argued that the gender gap in skill use at work cannot be explained by differences in job characteristics or by differences in cognitive test scores but it disappears once we control for the hours spent on housework and skill use in leisure time. Our preferred explanation for these empirical facts is a self-enforcing equilibrium where activities at the workplace and in leisure time are determined simultaneously.

Our argument is based on the theoretical model of Albanesi and Olivetti (2009). In their model, workers have capacity constraint in making an effort and they can divide their efforts between the workplace and home production. Employees cannot observe the effort of their workers but they assume that women are more willing to exert more effort in home production and they are less willing or less able to make high levels of effort at the workplace. Under these assumptions, firms are less likely to incentivize woman to make high effort. Moreover, thisdiscriminative assumption is self-enforcing (Loury, 2009). Once women observe the discrimination against them they translate their effort to home production even if ex ante they had the same preferences as men. The authors also test the model empirically by comparing it by occupations and show that the gender wage gap is the highest in occupations where incentive wages are most prevalent[13].

Similarly to Albanesi and Olivetti (2009), we argue that statistical discrimination is one of the reasons why women use their cognitive skills less at the workplace. Since employers may assume that women are less likely to make high effort at the workplace, firms tend to assign easily monitorable and less skill intensive tasks to women. Women observe the discrimination and the lower return to their effort at the workplace. As a consequence they are less willing to do overtime hours and more willing to do housework. Finally, it is also plausible to assume that skill use in leisure time and at the workplace are complements. More specifically, people who develop the habit of reading or using computers a lot at their workplace are more willing to read and use computers in their leisure time as well. If this is true then labor market discrimination against women leads to a lower amount of skill use in leisure time as well.

We augment the results of Albanesi and Olivetti (2009) along several dimensions. First of all, we use direct measures of individual effort. It is plausible to assume that skill use at work and

[13] We re-estimated our main regressions aon a sub-sample where workers did not receive incentive wage components. The results were virtually the same so we do not show the results.

working hours are good proxies of effort at the workplace while the hours spent on housework proxies the effort spent on home production. That is why we conclude that women translate a larger share of their total effort to home production than men. Second, we can compare the effort level of individuals not only between occupations but also within occupations. This enables us to control for the tasks and duties that workers should fulfill based on their job descriptions. Furthermore, we control for the numeracy and literacy test scores of individuals so we can show that the lower cognitive skill use of women is not driven by lack of skills. As a consequence, we can interpret our empirical findings as suggestive evidence of statistical discrimination.

4.1 Alternative explanations

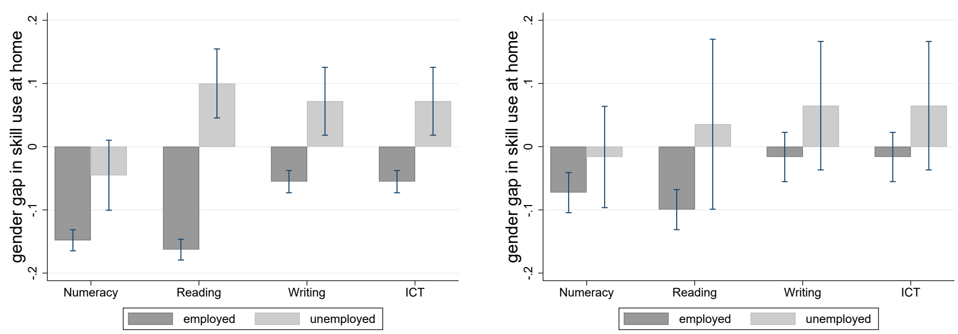
In this section we investigate and rule out four alternative mechanisms which could lead to lower skill use by women even after we have controlled for occupation and cognitive abilities. These are: (i) possibilty that women have different preferences towards skill use than otherwise similar men; (ii) women have lower bargaining power within the household and at the workplace; (iii) discriminative assumptions about the cognitive skills of women; and (iv) discrimination based on birth rates.

Gender differences in skill use preferences. It would be a heroic assumption that men and women have the same preferences regarding cognitive skill use or housework. That is why we simply argue that gender differences in preferences cannot fully explain our empirical findings. First of all, women might prefer to use cognitive skills less often than men. As a consequence, women may use their skill less at the workplace and at home even if there is no labor market discrimination. Furthermore, the skill use at home may be merely a proxy of individual preferences toward skill use in this scenario. To test this hypothesis we compare the gender gap in skill use in leisure time among the employed and the unemployed. If skill use in leisure time were merely a proxy of individual preferences toward skill use then the gender gap in skill use in leisure time should be the same among the employed and the unemployed. The consequence of our preferred explanation is different: we expect that labor market discrimination alters the habit of using skills in leisure time of working women and we expect *lower* gender gap in skill use in leisure time among the unemployed as their habit of using skills are not affected by workplace discrimination.

Figure 3 summarizes the gender gap in skill use at home among the employed and the unemployed. Skill use at home is standardized to have a mean of zero and a standard deviation of one. The left panel highlights that women use their numeracy and reading skills with 0.15 standard deviation less than employed men; and the gap is somewhat smaller in writing and ICT skills. Contrary to the above potential alternative mechanism, we find that the gender gap in numeracy skill use is much smaller among the unemployed. Additionaly, unemployed women tend to use their reading, writing and ICT skills more than unemployed men. We find similar patterns if we control for age, years of education and cognitive test scores[14]: the gender gap in skill use at home is more negative among the employed than among the unemployed in every skill use measure. Based on these results, we reject the hypothesis that women use their skills less often at the workplace only because they have different skill use preferences than men.

Figure 3. Gender gap in skill use in leisure time among the employed and the unemployed

(a) Raw difference (b) Conditional difference



Notes: The figure shows the gender gap in skill use in leisure time amongthe employed and the unemployed. Skill use in leisure time is standardized to have a mean of zero and a standard deviation of one. Negative numbers mean that women use their cognitive skills less in leisure time. The left panel shows the raw gap in skill use while the right panel controls for age, age-square, years of education, and numeracy and literary test scores. The figure highlights that employed women use their skills less in leisure time than employed men while we do not observed such a difference among the unemployed.

There may also be gender differences in the marginal cost of doing housework. More precisely, women may generally suffer lower disutility from doing housework than men. As a consequence, women spend more hours on housework and because of their capacity constraints, they are less able to make high effort or use cognitive skills both at the workplace and in leisure time. Furthermore,

[14]The numeracy and literacy test scores over-control for the gender gap in skill use at home as the frequency of using skills at home may increase cognitive test scores.

this mechanism may hold even if firms do not allocate task discriminatively.

Table 6. The effect of housework and family care on skill use at work

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Numeracy skill use at work			**Literacy skill use at work**			**ICT skill use at work**		
Gender gap	-0.007	-0.032*	-0.002	0.005	-0.024	0.012	0.061***	0.012	0.062***
	(0.021)	(0.018)	(0.023)	(0.018)	(0.017)	(0.018)	(0.016)	(0.016)	(0.016)
Housework	-0.004**		-0.006**	-0.006***		-0.007***	-0.010***		-0.010***
	(0.002)		(0.002)	(0.001)		(0.001)	(0.002)		(0.002)
Family care		-0.001	0.000		0.000	0.001**		-0.001	0.001
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Control variables differ by column. The main control variables are working hours and the standardized indices measuring skill use in leisure time. The additional control variables are the same as in Table 4 Column (3): partner dummy, child dummy, years of education, experience, experience^2, cognitive test results, occupation categories (ISCO 3 digit), country fixed effects, parents' highest level of education and parents' immigration status, dummy for full time work, self-employment dummy, dummy for having a permanent contract, dummies for 1 digit industry, 5 firm size categories, private sector and a set of social skills (categorical variable for cultural engagement, political efficacy, social trust, social trust 2 and health status). Standard errors are calculated with the jackknife method (suggested by OECD, 2013) using 80 replication weights. All of the the results are calculated by using sampling weights provided by the survey.

We can test this hypothesis by estimating the effect of family care[15] on workplace effort. If women were to use cognitive skills less at the workplace because they are tired as a result of the activities performed at home, then both family care and housework should crowd out the workplace effort of women.[16] In order to test this hypothesis, Table 6 estimates the effect of housework and family care on skill use at the workplace. Column (1) shows that one additional hour of housework decreases numeracy skill use by 0.004 standard deviation conditional on occupation, cognitive test scores and skill use in leisure time.[17] Furthermore Column (4) and (7) highlight that housework decreases literacy and ICT skill use even more. As opposed to this, hours spent on family care do not effect skill use at the workplace. The point estimates are very close to zero and are not

[15]Cubas et al. (2017) showed that hours spent on family care decreases wages especially in occupations where work hours are concentrated at peak times of the day.

[16]An implicit assumption in this exercise is that both family care and housework make people tired. We also test this using the ISSP survey, which explicitly asks respondents how often they are too tired to work properly at their workplace. Appendix Table **??** shows that both family care and housework make people tired: people spending more time on these activities are also more likely to be too tired to "concentrate" or to "function at job".

[17]The average amount of housework per week is 7 hours for men and 14 hours for women.

statistically significant. Finally, the results remain virtually the same if we jointly estimate the effect of housework and family care on skill use at work. This evidence suggests that women do not use their skills less at the workplace because they are too tired after doing their housework duties.

Bargaining within the household and at the workplace. It is possible that men earning higher salaries than their spouses are less willing to participate in the housework, which results in the women's inability to exert equal effort at the workplace. As a consequence, women end up doing less overtime and using their cognitive skills less often then similar men even if they are not discriminated against at the workplace. If this were the main reason of the gender gap in skill use, than we would expect no gender gap in skill use at work and in housework among workers who do not have a partner. As opposed to this, we find that single women do more housework than single men (weekly 10.6 vs 7.9 hours) and the coefficients of Table 5 do not change much if we omit workers who have partners (Table 7).

Table 7. Gender differences in skill use among single workers

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Numeracy skill use at work			
Gender gap	-0.240***	-0.256***	-0.143***	-0.177***	-0.164***	-0.161***
	(0.040)	(0.035)	(0.032)	(0.034)	(0.033)	(0.033)
			Panel B: Literacy skill use at work			
Gender gap	-0.147***	-0.116***	-0.013	-0.206***	-0.198***	-0.090***
	(0.044)	(0.039)	(0.032)	(0.033)	(0.032)	(0.030)
			Panel C: ICT skill use at work			
Gender gap	-0.086**	-0.081**	0.066**	-0.010	0.004	0.098***
	(0.033)	(0.031)	(0.029)	(0.033)	(0.033)	(0.032)
Working hours	YES	YES	YES	YES	YES	YES
Housework		YES	YES		YES	YES
Skill use in leisure time			YES			YES
Additional controls				YES	YES	YES

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Control variables differ by column. The main control variables are the working hours, hours spent on housework and the standardized indices measuring skill use in leisure time. The additional control variables are the same as in Table 4 Column (3): partner dummy, child dummy, years of education, experience, experience^2, cognitive test results, occupation categories (ISCO 3 digit), country fixed effects, parents' highest level of education and parents' immigration status, dummy for full time work, self-employment dummy, dummy for having a permanent contract, dummies for 1 digit industry, 5 firm size categories, private sector and a set of social skills (categorical variable for cultural engagement, political efficacy, social trust, social trust 2 and health status). Standard errors are calculated with the jackknife method (suggested by OECD, 2013) using 80 replication weights. All of the the results are calculated by using sampling weights provided by the survey.

Discriminative assumptions about cognitive skills. One reason why employers may assign less skill intensive tasks to women is because they assume that women have inferior cognitive skills compared to men. Altonji and Pierret (2001) studied this issue and found that employers observe individual skills with a delay but they discriminate less and less over time based on easily observable characteristics. It follows from their argument that cognitive skills have an increasing effect on skill use at work as time goes on, while easily observable characteristics (e.g. gender) have a decreasing effect. We can also formalize the argument and estimate the following regression:

$$y_i = \beta_0 + \beta_1 * female_i + \beta_2 * female_i * exp_i + \beta_3 * skill_i + \beta_4 * skill_i * exp_i + \gamma * X_i + u_i \quad (2)$$

Similarly to Equation 1, the dependent variable is cognitive skill use at work. Exp_i denotes the labor market experience of workers while $skill_i$ denotes the cognitive test scores. If women are discriminated because they are assumed to have lower skills then β_4 is positive and β_2 increases once we add β_4 to the regression (Altonji and Pierret, 2001).

The estimation results are shown in Table 8. Contrary to the predictions of this alternative mechanism, the effect of skills does not increase with experience and the gender gap in skill use does not decrease faster once we control for the dynamic effects of cognitive skills. We can conclude that women are not assigned to tasks requiring lower skills because they are assumed to have lower skills.

Table 8. Discriminative assumptions about cognitive skills

	(1)	(2)	(3)	(4)	(5)	(6)
	Numeracy skill use		Literacy skill use		ICT skill use	
Years of education	0.029***	0.029***	0.074***	0.074***	0.067***	0.067***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Female	-0.348***	-0.352***	-0.288***	-0.291***	-0.303***	-0.310***
	(0.040)	(0.040)	(0.042)	(0.044)	(0.038)	(0.039)
Experience	0.004**	0.004**	-0.000	-0.000	0.003	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female*experience	-0.001	-0.001	0.008***	0.008***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Numeracy test score	0.137***	0.129***	-0.012	-0.025	0.007	-0.011
	(0.033)	(0.045)	(0.025)	(0.048)	(0.034)	(0.046)
Num. test score*experience		0.000		0.001		0.001
		(0.002)		(0.002)		(0.002)
Literacy test score	-0.053	-0.071	0.037	0.046	0.043	0.024
	(0.033)	(0.052)	(0.023)	(0.044)	(0.029)	(0.048)
Lit. test score*experience		0.001		-0.001		0.001
		(0.003)		(0.002)		(0.002)
Observations	21,133	21,133	21,133	21,133	21,133	21,133
R-squared	0.045	0.045	0.069	0.069	0.055	0.056

The table shows the point estimates for Equation 2. The dependent variables are shown at the top of the column. The control variables are the same as in Table 4; partner dummy, child dummy, years of education, experience, experience^2, cognitive test results, occupation categories (ISCO 3 digit), country fixed effects, parents' highest level of education and parents' immigration status, dummy for full time work, self-employment dummy, dummy for having a permanent contract, dummies for 1 digit industry, 5 firm size categories, private sector and a set of social skills (categorical variable for cultural engagement, political efficacy, social trust, social trust 2 and health status). Standard errors are calculated with the jackknife method (suggested by OECD, 2013) using 80 replication weights. All of the results are calculated by using sampling weights provided by the survey.

Discrimination based on expectations of childbirth. Some employers may offer less skill intensive tasks to workers who are expected to stay with the firm for a shorter period of time. As a consequence, employers may discriminate against women because they more likely to exit the firm for maternity leave (Yip and Wong, 2014). To test this hypothesis we organize workers in labor market segments by country, education and age, and merge the segment specific birth rates from the Human Fertility Database.[18] Using the merged database we run the following regression:

$$y_i = \beta_0 + \beta_1 * female_i + \beta_2 * fertillty_c + \beta_3 * female_i * fertillty_c + \gamma * X_i + u_i \tag{3}$$

Again, the left hand-side variables are the skill use indices at work. $Fertility_c$ denotes the country-education-age specific birth rates while X_i are the same control variables as in equation 1. The parameter of $fertility_c$ measures the effect of women's fertility rate on men in the same demographic segment.[19] This parameter can even be positive if firms allocate the skill intensive tasks from women to men more in higher fertility rate segments[20]. Our main variable of interest is β_3, which is negative if women of a larger fertility rate cohort are assigned with less skill intensive tasks. We consider this parameter as the measure of statistical discrimination, as it shows the effect of the average behavior of the labor market segment on individual outcomes.

The point estimates for Equation 3 show mixed results (Table 9). The estimated effect of women's fertility rate on men (β_2), varies a lot between the skill use indices and they are highly sensitive to the inclusion of control variables, but are mostly positive. As the average fertility rate in our sample is 0.03, the estimated parameters seems to have a very low effect on the skill use of men.

Turning to the main variable of interest, Column (2) shows that the fertility rate decreases the numeracy skill use of women compared to men of the same age and educational level. Again, the point estimates are low, as the gender gap in skill use would decrease only with 0.823*0.03=0.024 if the birth rate decreased to zero. Moreover, Column (4) reveals that the birth rate does not decrease

[18] The data are available at the homepage of Human Fertility Database: http://www.humanfertility.org/cgi-bin/main.php

[19] As the fertility rate is defined for women only, we merge women's fertility by country-education-age to the data. e.g.: in the case of a 27-year-old Italian men with a university degree, this parameter shows the effect of the fertility rate of a similar Italian woman (27-years-old with a university degree)

[20] This may be the case if workers with different skill levels and young and old workers are not perfect substitutes (Card and Lemieux, 2001) but women and men of the same age and skills are close substitutes.

significantly the literacy skill use of women. The point estimate is negative but statistically not different from zero (coef. -0.68 s.e 0.49). Finally, we do not find a significant negative relationship between the fertility rate and ICT skill use of women (coeff 0.85 s.e. 0.46) either once we control for individual characteristics in Column (6). Based on these results, we conclude that discrimination based on cohort specific fertility rates cannot explain the gender gap in skill use.

Table 9. The effect of birth rate on the gender gap in skill use

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Numeracy skill use		Literacy skill use		ICT skill use	
Gender gap	-0.311***	-0.140***	-0.353***	-0.193***	-0.335***	-0.163***
	(0.028)	(0.027)	(0.025)	(0.027)	(0.024)	(0.027)
Fertility rate	0.521	1.133***	-1.663***	1.409***	0.407	1.055***
	(0.366)	(0.371)	(0.367)	(0.428)	(0.393)	(0.380)
Fertility rate*women	-0.194	-0.823**	0.980*	-0.679	1.785***	0.852*
	(0.522)	(0.404)	(0.498)	(0.485)	(0.493)	(0.465)
Controls		YES		YES		YES
Observations	21,130	21,130	21,130	21,130	21,130	21,130
R-squared	0.025	0.223	0.028	0.207	0.022	0.273

Notes: The table shows the point estimates for Equation 3. The dependent variables are shown at the top of the column. The control variables are the same as in Table 4: partner dummy, child dummy, years of education, experience, experience^2, cognitive test results, occupation categories (ISCO 3 digit), country fixed effects, parents' highest level of education and parents' immigration status, dummy for full time work, self-employment dummy, dummy for having a permanent contract, dummies for 1 digit industry, 5 firm size categories, private sector and a set of social skills (categorical variable for cultural engagement, political efficacy, social trust, social trust 2 and health status). Standard errors are calculated with the jackknife method (suggested by OECD, 2013) using 80 replication weights. All of the results are calculated by using sampling weights provided by the survey.

5 Conclusion

Although a large body of empirical literature documents the gender differences prevailing on the labor market, we know much less about what people actually do at their workplace and what causes the within occupational gender differences. To the best of our knowledge we are the first to document within occupation differences in skill use and to examine the underlying mechanisms at the same time.

By using an international survey (PIAAC - Programme for the International Assessment of Adult Competencies) that provides detailed information on tasks performed during work, we found that women report significantly lower levels of numeracy and computer skill usage and they also read and write significantly less at the workplace than men do. This finding is robust against taking into account the composition effects (demographic and firm characteristics, different levels of education and experience) and controlling for social and cognitive skill differences. We argue that the most important predictor of the gap in the skill intensity of jobs across genders is that women do less overtime but do more housework and they use their cognitive skills less even in their everyday lives. Since our finding is robust even after controlling for cognitive test scores we argue that this difference cannot be contributed to the lack of capability.

We argue that these empirical facts can be explained by statistical discrimination against women. More precisely, employers assume that women are more willing to make a higher effort in leisure time and a lower effort at the workplace than otherwise identical men. That is why firms assign easily monitorable, less skill intensive tasks to women. Women observe this kind of discrimination and they translate their efforts to home production even if they have the same preferences as men.

Finally, our results imply that labor market discrimination may affect activities outside the labor market as well, and policies which aim to decrease gender segregation between occupations cannot, in themselves, eliminate gender differences on the labor market.

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Appendix

Table A-1. The construction of skill use indices

(a) Cognitive skill use indices

Index of use of numeracy skills at work
How often - Calculating costs or budgets
How often - Use or calculate fractions or percentages
How often - Use a calculator
How often - Prepare charts graphs or tables
How often - Use simple algebra or formulas
How often - Use advanced math or statistics

Index of use of writing skills at work
How often - Write letters memos or mails
How often - Write articles
How often - Write reports
How often - Fill in forms

Index of use of reading skills at work
How often - Read directions or instructions
How often - Read letters memos or mails
How often - Read newspapers or magazines
How often - Read professional journals or publications
How often - Read books
How often - Read manuals or reference materials
How often - Read financial statements
How often - Read diagrams maps or schematics

Index of use of ICT skills at work
How often - For mail
How often - Work related info
How often - Conduct transactions
How often - Spreadsheets
How often - Real-time discussions

(b) Non-cognitive skill use indices

Index of use of planning skills at work
How often - Planning own activities
How often - Planning others' activities
How often - Organizing own time

Index of use of influencing skills at work
How often - Teaching people
How often – Presentations
How often - Advising people
How often - Planning others' activities
How often - Influencing people
How often - Negotiating with people

Index of learning at work
How often - Learning from co-workers/supervisors
How often - Learning - Learning-by-doing
How often - Learning - Keeping up to date

Index of use of task discretion at work
Work flexibility - Sequence of tasks
Work flexibility - How to do the work
Work flexibility - Speed of work
Work flexibility - Working hours

Table A-2. Gender gap in skill use by country

	(1)		(2)		(3)	
Country	Numeracy		Literacy		ICT	
	coeff.	(s.e.)	coeff.	(s.e.)	coeff.	(s.e.)
Czech Republic	-0.057	(0.078)	-0.239***	(0.064)	-0.021	(0.066)
Denmark	-0.250***	(0.045)	-0.192***	(0.044)	-0.183***	(0.041)
France	-0.176***	(0.036)	-0.185***	(0.030)	-0.030	(0.037)
Great-Britain	-0.182***	(0.049)	-0.157***	(0.042)	-0.089*	(0.051)
Germany	-0.154***	(0.053)	-0.219***	(0.044)	-0.066	(0.049)
Japan	-0.217***	(0.039)	-0.207***	(0.045)	-0.205***	(0.048)
Republic of Korea	-0.141***	(0.038)	-0.128***	(0.044)	-0.086*	(0.049)
Norway	-0.350***	(0.041)	-0.282***	(0.040)	-0.195***	(0.035)
Poland	-0.100**	(0.048)	-0.093*	(0.053)	-0.132**	(0.061)
Russia	0.052	(0.080)	-0.048	(0.068)	-0.138***	(0.049)
Slovakia	-0.061	(0.055)	-0.091*	(0.050)	0.022	(0.051)
Spain	-0.158***	(0.051)	-0.252***	(0.051)	-0.247***	(0.054)

Notes: The columns show the gender gap by skill use indices. Every row consists regressions for the given country. Every regression controls for years of education and standardized literacy and numeracy skills, for partner dummy, child dummy, years of education, experience, experience^2, occupation categories (ISCO 3 digit), parents' highest level of education and parents' immigration status, dummy for full time work, self-employment dummy, dummy for having a permanent contract, dummies for 1 digit industry, 5 firm size categories, private sector and a set of social skills (categorical variable for cultural engagement, political efficacy, social trust, social trust 2 and health status). Standard errors are calculated with the jackknife method (suggested by OECD, 2013) using 80 replication weights. All of the the results are calculated by using sampling weights provided by the survey. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table A-3. The effect of housework on skill use at work

Panel A: Numeracy skill use at work				
Female	-0.138***	-0.078***	-0.075***	-0.007
	(0.021)	(0.020)	(0.022)	(0.021)
Working hours	0.012***	0.017***	0.009***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
Housework	-0.010***	-0.006***	-0.004**	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
Panel B: Literacy skill use at work				
Female	-0.031	0.006	-0.084***	0.005
	(0.022)	(0.017)	(0.022)	(0.018)
Working hours	0.014***	0.020***	0.011***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)
Housework	-0.023***	-0.010***	-0.006***	-0.006***
	(0.002)	(0.001)	(0.002)	(0.001)
Panel C: ICT skill use at work				
Female	-0.108***	-0.016	-0.040**	0.061***
	(0.019)	(0.018)	(0.019)	(0.016)
Working hours	0.010***	0.015***	0.008***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Housework	-0.015***	-0.011***	-0.009***	-0.010***
	(0.002)	(0.001)	(0.002)	(0.002)
Skill use in leisure time		YES		YES
Additional controls			YES	YES

Notes: The table mimics Columns (2), (3), (5), (6) of Table 5. The main message of the table is that the coefficient of housework remains similar once we control for skill use in leisure time. The additional control variables are the same as in Table 5 Column (3): partner dummy, child dummy, years of education, experience, experience^2, cognitive test results, occupation categories (ISCO 3 digit), country fixed effects, parents' highest level of education and parents' immigration status, dummy for full time work, self-employment dummy, dummy for having a permanent contract, dummies for 1 digit industry, 5 firm size categories, private sector and a set of social skills (categorical variable for cultural engagement, political efficacy, social trust, social trust 2 and health status). Skill use in leisure time is measusure with standardized indices on the skill use in leisure time. Standard errors are calculated with the jackknife method (suggested by OECD, 2013) using 80 replication weights. All of the the results are calculated by using sampling weights provided by the survey. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table A-4. Skill intensity of the job and activities in leisure time - blue collar jobs

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Numeracy skill use at work					
Gender gap	-0.089***	-0.019	-0.011	-0.152***	-0.108***	-0.104**
	(0.026)	(0.033)	(0.046)	(0.024)	(0.034)	(0.044)
	Panel B: Literacy skill use at work					
Gender gap	-0.170***	-0.032	-0.019	-0.185***	-0.142***	-0.074*
	(0.026)	(0.039)	(0.038)	(0.036)	(0.044)	(0.041)
	Panel C: ICT skill use at work					
Gender gap	-0.178***	-0.135***	-0.031	-0.165***	-0.123***	-0.033
	(0.039)	(0.038)	(0.038)	(0.037)	(0.038)	(0.041)
Working hours	YES	YES	YES	YES	YES	(0.037)
Housework		YES	YES		YES	YES
Skill use in leisure time			YES			YES
Additional controls				YES	YES	YES

Notes: Control variables differ by column. The additional control variables are the same as in Table 5 Column (3): partner dummy, child dummy, years of education, experience, experience^2, cognitive test results, occupation categories (ISCO 3 digit), country fixed effects, parents' highest level of education and parents' immigration status, dummy for full time work, self-employment dummy, dummy for having a permanent contract, dummies for 1 digit industry, 5 firm size categories, private sector and a set of social skills (categorical variable for cultural engagement, political efficacy, social trust, social trust 2 and health status) Standard errors are calculated with the jackknife method (suggested by OECD, 2013) using 80 replication weights. All of the the results are calculated by using sampling weights provided by the survey. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table A-5. Non-cognitive skill use at work

	(1)		(2)		(3)	
Panel A: use of planning skills at work						
	coeff.	(s.e.)	coeff.	(s.e.)	coeff.	(s.e.)
Gender Gap	-0.154***	(0.015)	-0.119***	(0.016)	-0.033**	(0.016)
Years of education			0.064***	(0.004)	0.019***	(0.004)
Literacy test scores			-0.015	(0.018)	0.020	(0.015)
Numeracy test scores			0.055***	(0.020)	0.042***	(0.016)
Panel B: use of influencing skills at work						
Gender Gap	-0.213***	(0.021)	-0.177***	(0.021)	-0.150***	(0.018)
Years of education			0.090***	(0.005)	0.032***	(0.005)
Literacy test scores			-0.051**	(0.020)	-0.037**	(0.018)
Numeracy test scores			0.079***	(0.023)	0.063***	(0.018)
Panel C: use of task discretion at work						
Gender Gap	-0.223***	(0.016)	-0.190***	(0.018)	-0.060***	(0.015)
Years of education			0.024***	(0.003)	0.010**	(0.004)
Literacy test scores			-0.005	(0.020)	0.015	(0.016)
Numeracy test scores			0.087***	(0.021)	0.015	(0.017)
Panel C: use of learning skills at work						
Gender Gap	-0.079***	(0.017)	-0.059***	(0.019)	-0.077***	(0.015)
Years of education			0.066***	(0.006)	0.032***	(0.005)
Literacy test scores			-0.009	(0.023)	0.025	(0.024)
Numeracy test scores			0.006	(0.026)	-0.004	(0.023)
Additonal controls						Yes

Notes: Control variables differ by column. Column (2) controls for years of education and standardized literacy and numeracy skills. The additional control variables are the same as in Table 5 Column (3): partner dummy, child dummy, years of education, experience, experience^2, cognitive test results, occupation categories (ISCO 3 digit), country fixed effects, parents' highest level of education and parents' immigration status, dummy for full time work, self-employment dummy, dummy for having a permanent contract, dummies for 1 digit industry, 5 firm size categories, private sector and a set of social skills (categorical variable for cultural engagement, political efficacy, social trust, social trust 2 and health status). Standard errors are calculated with the jackknife method (suggested by OECD, 2013) using 80 replication weights. All of the the results are calculated by using sampling weights provided by the survey. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

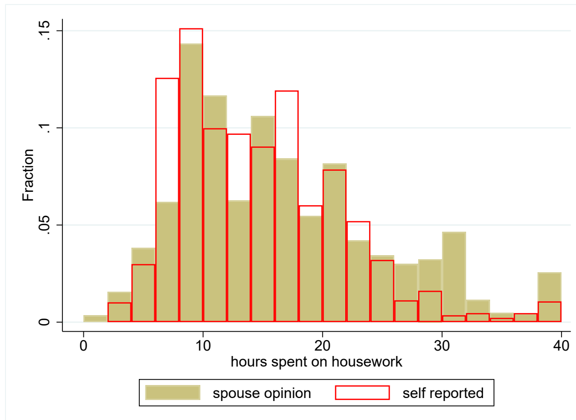
Table A-6. Effect of activities at home on tiredness at work

	(1)	(2)	(3)	(4)
	„never too tired to function in job”		„never too tired to concentrate”	
family care	*-0.002******	-0.002***	*-0.004******	*-0.004******
	(0.000)	(0.000)	*(0.000)*	*(0.000)*
housework	*-0.006******	-0.004***	*-0.002******	*-0.002******
	(0.001)	(0.001)	*(0.001)*	*(0.001)*
Controls		YES		YES
Observations	9,017	9,017	8,967	8,967
R-squared	0.028	0.080	0.022	0.051

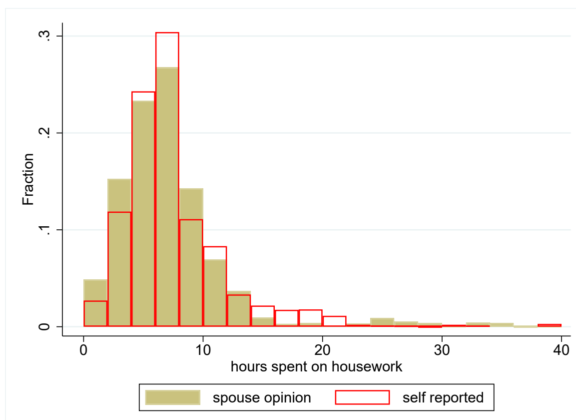
Notes: This table estimates the effect of household activities on tiredness at the workplace. The dependent variable of Columns (1) and (2) is one if the respondent is “never too tired to function in the job”. The dependent variable of Column (3) and (4) is one if the respondent is “never too tired to concentrate”. The main variable of interest is the number of hours spent on family care and on housework. The other control variables are age and dummy variables for having a partner, highest educational level, country and three digit occupational category. The table highlights that hours spent both on family care and on housework decrease the probability of never being too tired to work. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Figure A-1. The self reported and spouse reported hours spent on housework (weekly hours)

females



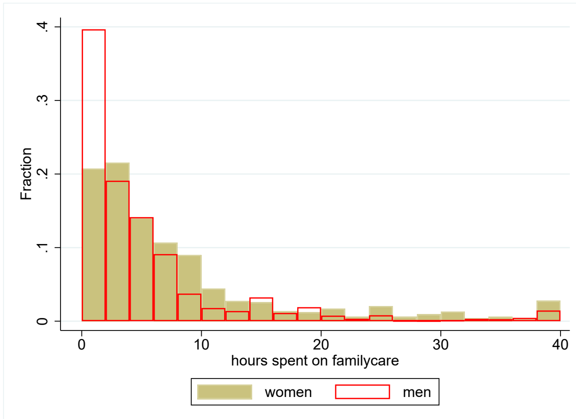
males



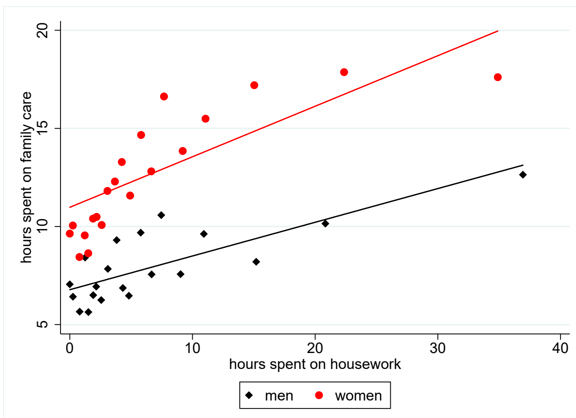
Notes: The figure shows that the self reported and spouse reported hours spent on housework are similar. Single households are omitted and hours spent on housework are winsorized at 40 hours.

Figure A-2. Distribution of family care (weekly hours)

Panel A: hours spent on family care



Panel B: amount family care by the hours spent on housework

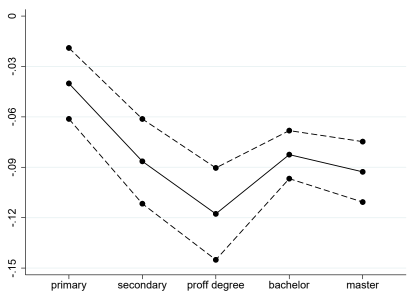


Notes: Panel A shows the distribution of hours spent on family care. Panel B shows the average hours spent on family care as the function of hours spent on housework. Both the hours spent on housework and family care are winsorized at 40 hours.

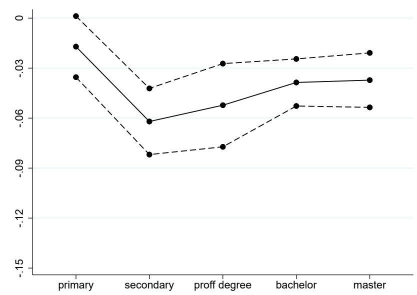
Figure A-3. The gender gap in skill use by educational level

Panel A: Gender gap in numeracy skill use at work

unconditional gap

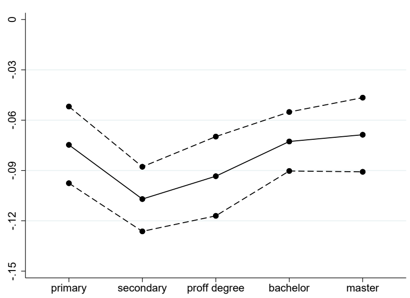


conditional gap

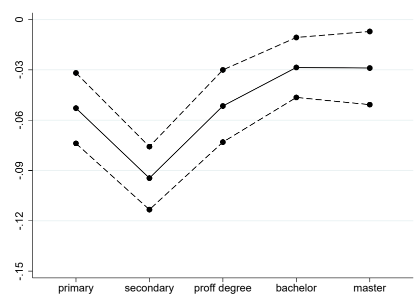


Panel B: Gender gap in literacy skill use at work

unconditional gap

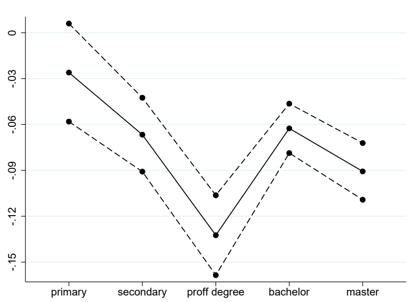


conditional gap

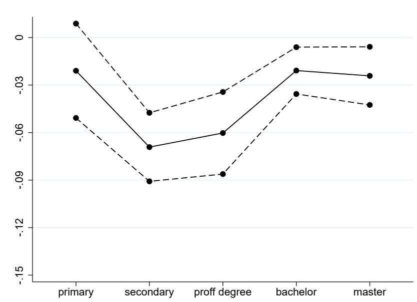


Panel C: Gender gap in ICT skill use at work

unconditional gap



conditional gap

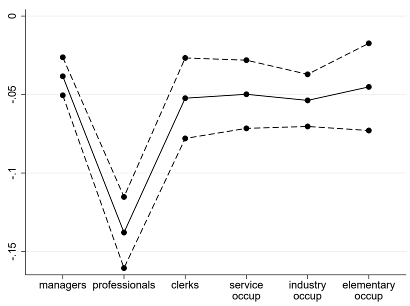


Notes: The figure shows the gender gap in cognitive test scores by educational level. The figures on the left show the raw gap while the figures on the right use the same control variables as in Table 5 Column (3): partner dummy, child dummy, years of education, experience, experience^2, cognitive test results, occupation categories (ISCO 3 digit), country fixed effects, parents' highest level of education and parents' immigration status, dummy for full time work, self-employment dummy, dummy for having a permanent contract, dummies for 1 digit industry, 5 firm size categories, private sector and a set of social skills (categorical variable for cultural engagement, political efficacy, social trust, social trust 2 and health status). Standard errors are calculated with the jackknife method (suggested by OECD, 2013) using 80 replication weights. All of the the results are calculated by using sampling weights provided by the survey.

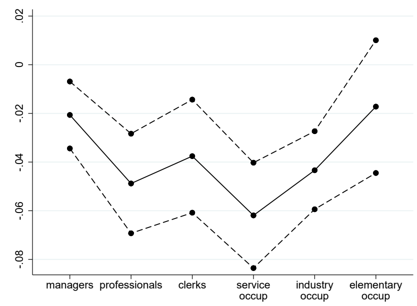
Figure A-4. The gender gap in skill use by occupation groups

Panel A: Gender gap in numeracy skill use at work

unconditional gap

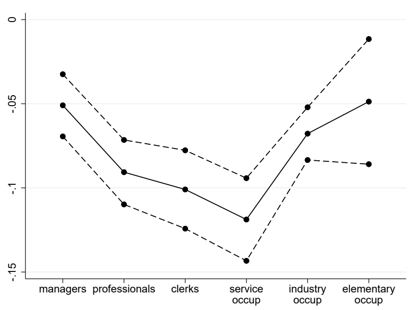


conditional gap

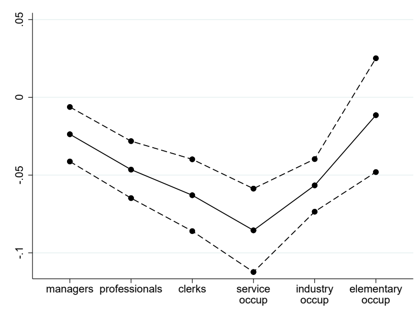


Panel B: Gender gap in literacy skill use at work

unconditional gap

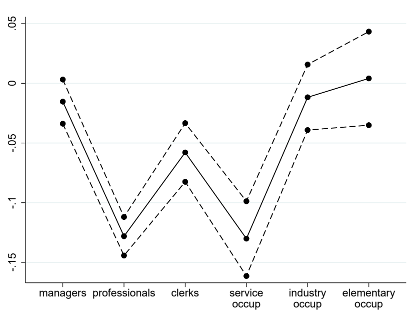


conditional gap

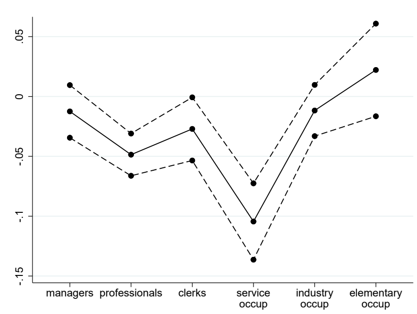


Panel C: Gender gap in ICT skill use at work

unconditional gap



conditional gap

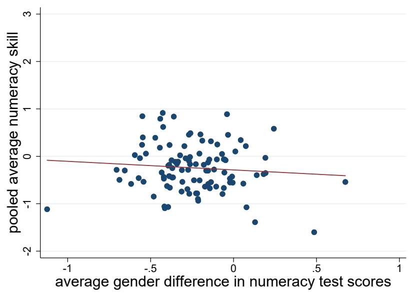


Notes: The figure shows the gender gap in cognitive test scores by occupational categories. The figures on the left show the raw gap while the figures on the right use the same control variables as in Table 5 Column (3): partner dummy, child dummy, years of education, experience, experience^2, cognitive test results, occupation categories (ISCO 3 digit), country fixed effects, parents' highest level of education and parents' immigration status, dummy for full time work, self-employment dummy, dummy for having a permanent contract, dummies for 1 digit industry, 5 firm size categories, private sector and a set of social skills (categorical variable for cultural engagement, political efficacy, social trust, social trust 2 and health status). Standard errors are calculated with the jackknife method (suggested by OECD, 2013) using 80 replication weights. All of the the results are calculated by using sampling weights provided by the survey.

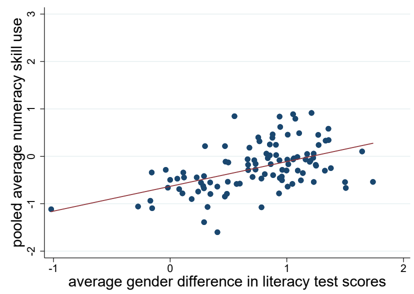
Figure A-5. Average skill use and gender gap test scores by occupations

Panel A: numeracy skill use at work by gender gap in cognitive skills

numeracy test scores

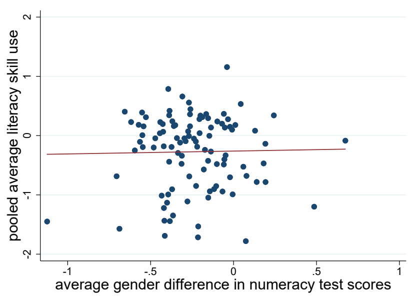


literacy test scores

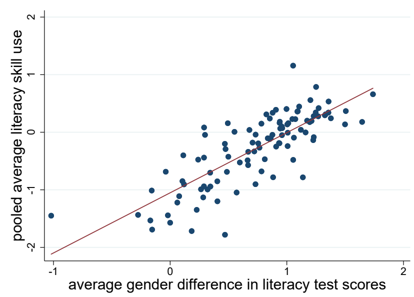


Panel B: literacy skill use at work by gender gap in cognitive skills

numeracy test scores

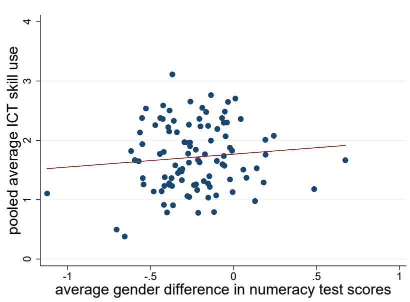


literacy test scores

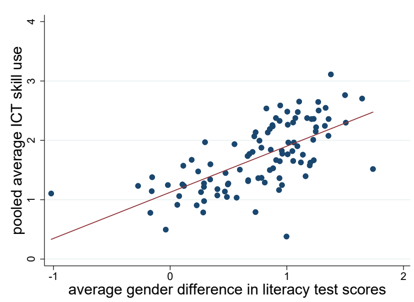


Panel C: ICT skill use at work by gender gap in cognitive skills

Numeracy test scores



literacy test scores



Notes: The figure shows the average skill use in a given occupation (vertical axis) by the gender gap in cognitive test scores (horizontal axis) in a given occupation. Every dot represents an occupation defined by 3-digit ISCO codes. Control variables are the same as in Table 4 Column (3). Standard errors are calculated with the jackknife method (suggested by OECD, 2013) using 80 replication weights. All of the the results are calculated by using sampling weights provided by the survey.