SWEDISH ECONOMIC POLICY REVIEW 14 (2007) 151-189

Are women falling behind in the new economy? Gender gaps in new skills and competencies

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Summary

■ Where traditionally literacy and numeracy skills were adequate for assembly-line work, more informal and general skills such as communication, problem-solving, self-management and life-long learning are being valued by the knowledge economy. Moreover, the diffusion of IT and increased global competition require computer proficiency and English language literacy from workers. Yet the available evidence suggests that a large fraction of the workforce, particularly women and minorities, may be trailing behind in acquiring such skills and capturing the employment and wage gains associated with them. I use a unique Danish representative survey, the National Competence Accounts (NKR) 2004, to explore, first, whether there exist significant gender gaps in the levels of new skills and competencies, second, whether these gaps are linked to women's job position in a segregated labor market, and third, whether men and women receive the same wage returns to investments in new skill acquisition. The estimates arising from a model of endogenous skill acquisition show that there are few gender gaps in the levels of competencies, but that men to a larger extent than women capture the wage gains associated with skill acquisition. Men appear to be rewarded for competencies which are more easily transferable across jobs and desirable at managerial levels, while women are rewarded instead for competencies which are more job-specific in nature and fit better at lower levels within the organization. Some additional investigations reveal that skill quality differences, skill mismatch, childcare responsibilities and differences in bargaining strengths account for part but not all of women's lower returns to competencies. ■

JEL classification: J16, J31, J7.
Key words: new skills and competencies, male-female wages, gender discrimination.

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Widespread diffusion of new technologies, massive inflows of information, global competition and organizational restructuring are the trademarks of the new economy. New technologies in turn require new skills and competencies of the workforce. Where traditionally literacy and numeracy skills were adequate for the purposes of operating machines or working on assembly lines, workers in the knowledge economy need to be able to communicate effectively, possess strong leadership skills, be good at problem-solving, proficient in the use of computers and engage in lifelong learning.

In the words of Alan Greenspan:

> *The heyday when a high school or college education would serve a graduate for a lifetime is gone; basic credentials, by themselves, are not enough to ensure success in the workplace...Workers must be equipped not simply with technical know-how but also the ability to create, analyze, and transform information and to interact effectively with others. Moreover, learning will increasingly be a lifelong activity.* (Structural change in the new economy, Remarks before the National Governor's Association, 92nd Annual Meeting, 2000).

Accordingly, formal qualifications and know-how tied to firm specificities are increasingly being replaced by more informal and general skill requirements encompassing broad or generic abilities referred to as "competencies" in the organizational performance literature.

At the same time, the available evidence suggests that a large fraction of the workforce, particularly women and minorities, may be trailing behind in acquiring and developing such skills or competen-

* *The author thanks Philip Røpcke for excellent research assistance. Participants at the Economic Council of Sweden's Conference on Gender and Ethnic Discrimination, Stockholm, October 30 and especially the discussant of the paper, Åsa Löfström, and an anonymous referee are thanked for their very valuable comments and suggestions.*

cies and in capturing the employment and wage gains associated with them (OECD, 2000).

According to Acemoglu's (1999) theory, in the presence of technological change, firms respond by changing the composition of their workforces, leading to a segmented labor market consisting of high-tech firms employing skilled workers and low-tech firms employing low-skilled workers. Such demand shifts have been found to be detrimental to the labor market position of black men as "soft" skills become increasingly more important to employers than test scores or technical know-how (Moss and Tilly, 1996). Evidence of a polarization of work along gender lines is provided by Echeverri-Carroll and Ayala (2006) who find based on the US 2000 Census of Population that high-tech industries mainly tend to employ skilled men and pay them a 12 percent higher wage than similarly qualified women. Datta Gupta and Eriksson (2006) show that the wage gains accruing to firms which adopt high performance work practices such as job rotation, quality circles or self-managed teams go mainly to their male employees, thereby widening firm-level gender pay gaps.

An alternative view to skill-biased technological change is that as a result of the expansion of tertiary education the growing supply of educated workers over time has outstripped the demand for educated labor, leading to over-qualification in the labor market. Further, this mainly affects groups such as women, while men tend to be more successful in obtaining jobs which are commensurate with their competences. Hartog (2000) provides evidence on over-education for a number of European countries, and le Grand et al. (2004) find that in the Swedish labor market mainly women and younger persons experience difficulties making correct job matches.

In a recent study of the evolution of the US gender wage gap, Blau and Kahn (2006) report that convergence in the pay gap slowed down in the 1990's compared to the 1980's. This slowdown cannot be attributed to traditional skill differences across the genders which continue to close rapidly over time, but rather to a combination of changing selectivity, changes in the favorableness of supply and demand shifts to female labor, and the increased importance of unobserved characteristics in the 1990's compared to the 1980's. In the European context as well, recent studies show a growing salience of unobserved factors in the gender pay gap, particularly in the upper tail of the distribution (Fitzenberger and Wunderlich, 2002, in the case of Germany; Albrecht et al, 2003, for Sweden; Datta Gupta et al., 2006, for

Denmark; and Arulampalam et al., 2007, for similar patterns in many other European countries, as well.)

A question arises, therefore, whether the growing importance of unobserved factors in the gap in wages between men and women in recent times can at least in part be due to differential rates of acquisition of/different rewards to the skills and competencies which are being demanded in the modern workplace, or by another interpretation, to a growing mismatch between the skills women possess and the jobs they hold. Such new competencies have not been incorporated into analyses of gender wage gaps before, and could be one reason for the persistence in the unexplained gap, i.e. new gender skill gaps emerge even as conventional gender skill gaps—in education and work experience—close.

I use a unique Danish representative survey, the National Competence Accounts (NKR) 2004, to explore whether, first, there exist significant gender gaps in the levels of new skills and competencies, second, whether these gaps are linked to women's job position in a segregated labor market, and third, whether men and women receive the same wage gains to investing in new skill acquisition.

The paper is laid out as follows: In the next section, I discuss decentralization and the gender wage gap. The unique data set used in this study is described in Section 2. Section 3 contains theoretical considerations, and Section 4 presents the empirical method. Descriptive statistics are discussed in Section 5, and the results from model estimation in Section 6. Section 7 includes further discussion, and Section 8 concludes.

1. Decentralization and the gender wage gap

In spite of the Danish gender wage gap being one of the lowest among industrialized countries, and the Danish wage distribution being relatively compressed in a global comparison, like many other welfare state nations, Denmark has experienced a growing decentralization in the wage setting process starting in the 1980's and continuing ever since. In a micro-study of 22 countries, Blau and Kahn (2003) show that highly centralized wage bargaining systems increase female wages relative to male wages by setting wage floors at the bottom of the distribution where women tend to be over-represented. Decentralization and the growing use of incentive-based pay systems, therefore, can adversely affect the gender wage gap by removing such centrally-determined wage floors. Another disadvantage for women arising from more individualized wage setting practices is that they have been found to lack negotiation skills. They are often reluctant to ask for pay increases or perquisites in bargaining situations vis-à-vis the employer, and Babcock and Laschever (2003) label this the "women don't ask" phenomenon. Yet another factor could be that when formal qualifications or objective performance criteria are replaced by soft skills and more subjective criteria, discrimination can take on more subtle and insidious forms, making it more difficult for women to seek legal recourse.

Since the 1980's and 1990's, the female-male wage ratio in Denmark has more or less stagnated at a constant level of 80-88 percent depending on whether straight wages or total compensation is used as the wage measure (Pedersen and Deding, 2002). Moreover, unlike some other countries, notably the US (Bayard et al., 2003), gender differences in pay in Denmark are considerably due less to variation across firms and more to variation within firms. A recent study by Datta Gupta and Rothstein (2005) utilizes matched employer-employee data and finds that the raw gender wage gap of manual and salaried workers fell from 27 and 47 percent respectively in 1983 to 20 and 41 percent respectively in 1995. The within-firm wage gap, estimated from wage equations with a female dummy and establishment fixed effects, turned out be quite close to the overall gap: for manual workers 25 and 17 percent in 1983 and 1995, respectively, and for salaried workers 46.5 and 40 percent in 1983 and 1995, respectively. The same study finds that occupation accounts for about half of the wage gap between male and female salaried employees. For manual employees, experience, industry and establishment accounts for about half. For both groups of employees, even after controlling for human capital differences, a significant gender differential remains within job cells (occupations within establishments). These findings provide additional motivation for examining divergences in wage-setting practices resulting in differing returns to new and more informal skills in the workplace.

2. Data

As part of an OECD project on Definition and Selection of Competencies, DeSeCo, 1998-2003, Denmark was one of 12 OECD countries to conduct a nationwide representative survey of individuals' competencies. In all, a representative sample of 7,954 individuals was contacted, of which 69.2 percent responded. The survey, which was conducted by telephone and carried out in the winter of 2003-04 by Statistics Denmark, also included labor market information on hours of work, tenure, occupation, industry, and annual income, as well as individual background characteristics such as gender, age, and education.

I employ eight core competencies in the analysis. Four competencies are those defined in the original OECD list: Communication, Innovation, Learning, and Self-Management. In addition, four other competencies are defined based on the questionnaire: Computer, Training, Mobility and English Language skills.[1]

A brief description of the eight competencies follows (see Appendix A for a detailed description of the factor analysis used to reduce the data to the eight broad categories):

- *Communication.* Using different forms of communication such as email, letters, telephone or the internet, giving oral presentations, engaging in verbal and written dialogue with colleagues involving work-related issues and improvements at the workplace.
- *Innovation.* Developing new ideas, new products or new work methods or finding solutions to problems, being in a workplace which emphasizes innovative thinking.
- *Computer.* Proficiency in the use of IT communication tools.
- *English Language.* Proficiency in spoken and written English.
- *Learning.* Trying out new methods, working in new teams or groups and being exposed to new technology.
- *Training.* Obtaining job training leading to new tasks and greater productivity.
- *Mobility.* Changed job function, participated in job rotation or taken a new job within the organization for the purpose of learning new skills.
- *Self-Management.* Having control over planning, organization and execution of one's job tasks, overview and influence over firm decision-making, flexibility with respect to work-life balance.

[1] Five other competences defined by the OECD included Social competence, Environmental competence, Health competence, Cultural competence, and Democratic competence. In a validation study of the NKR carried out by Mandat Analyse (2005), none of these five is found to be significantly related to workers' incomes, and they are therefore not included in the current analysis.

While this dataset affords unique information on new individual competencies, at least three shortcomings bear mentioning. First, the sample is small to start with, and due to missing information on a number of the survey questions used to construct the competencies, and on income, hours, firm size, and tenure, I end up with 3,616 usable observations.

Second, data are based on a single cross-section, therefore not allowing me to purge the estimates of bias arising from time-constant unobserved heterogeneity. This may be problematic if the wage returns to skills engendered by the diffusion of new technology merely reflect unobserved skills of the users of this technology, i.e., a spurious correlation (see, for example, DiNardo and Pischke, 1997, and Entorff and Kramarz, 1997, for studies which find this result for computer usage). I am partly able to get around this problem of omitted inherent ability by employing observed measures of literary and math ability as controls in the regressions.[2]

Thirdly, competencies are self-reported and may bias labor market outcomes such as wages, if systematic differences exist in individuals' self-reported competence based on their wages. If high-waged individuals over-report their competencies and/or low-waged individuals underreport them, then the effect of competencies on wages may be biased upward. There may in addition be differences by gender in reporting behavior (see Lindeboom and Van Doorslaer, 2004, in the area of health self-reporting, for example) which could be relevant. Men have been found to be more overconfident than women in investment decisions (Barber and Odean, 2001) and are perhaps more likely to overvalue their abilities than women in the setting of the present paper as well. In the survey, however, workers are queried rather specifically about the frequency or extent of use or application of a particular skill in the workplace, rather than about their rating on a general competency scale (see Appendix A for the actual wording of the questions in the survey). Therefore, I have less reason to believe that self-reporting imparts bias on the estimates in this case.

Finally, note that a "competence" in these data is some mix of individual abilities and the skills required on the job (see Appendix A). Thus, if individuals score low on a competence, say English language

[2] Studies show that standardized tests such as the SAT which include both verbal and math components appear to be good measures of general intelligence as they correlate well with IQ (see, for example, Frey and Detterman, 2004).

skills, this may reflect either that individuals have low English competence themselves or that the jobs they hold do not require English language usage. Therefore, instead of taking competences as given, I model them as being endogenously determined by relating them to the characteristics of the jobs individuals hold, the work they do, as well as their educational background and underlying abilities.

3. Theoretical considerations

The idea that general skills are becoming more important in the information economy and sector-specific skills (occupation, industry, job, etc.) less so has been convincingly demonstrated by Gould (2002), who shows that worker abilities have become more highly correlated across sectors over time. Even though workers may be sorting into different sectors according to comparative advantage, the economy is increasingly becoming characterized by absolute rather than comparative advantage, resulting in rising inequality. Lazear (2003) goes further, to say that all skills are general, because it is difficult to find credible examples of specific skills that could generate and sustain positive tenure coefficients. Firms could differ, however, in their weighting of different skills. In a setting where there are few alternative firms which employ the same weighting function ("thin markets"), Lazear's model predicts that workers' skill acquisition becomes more firm-idiosyncratic. This view of the labor market is also perfectly consistent with job matching (Jovanovich, 1979) or even the occupational investment theory (Shaw, 1984) because an occupation can be conceptualized merely as a particular weighting of a set of general skills, and a good job match could indicate that a worker possessing a particular combination of general abilities becomes employed at a firm that values exactly that combination.

The only difference then between a matching view of the labor market and the skills-weighted approach is that according to the latter, skills are acquired through investment on the job after the worker learns the firm's weighting function, whereas in the former, workers come to the labor market already endowed with a set of skills. The notion that at least some types of skills are best acquired on the job can be traced back to the ideas laid out by Becker in his book Human Capital (1964). More recently, Meng and Heijke (2005) model higher education as a production process in which different types of learning methods (attending formal educational courses, self-study, paid work) are modeled as inputs into the acquisition of competencies. Their results show that paid work is important for the acquisition of both generic competencies and discipline-specific competencies as long as there is a link between work and study, whereas formal education is important only for acquiring discipline-specific competencies. An illustrative example of new skill acquisition which is linked to the workplace is given by Bresnahan et al. (2002), who find that working in the ICT sector and knowledge industries and certain types of work practices foster the development of ICT technical skills.

Thus, the implications of theoretical models of the new economy and skill acquisition concur with the experience garnered by the organizational performance and HR practitioners that generic skills or broad competencies are becoming more important in the new economy and that, unlike traditional literacy and numeracy skills learned in the classroom or within the formal educational system, such competencies are, at least to some extent, acquired through work. A competing view is that skill-mismatch and not the nature of jobs themselves results in some groups of workers being incorrectly assigned to jobs which do not reward their competences (see for example Freeman, 1976; Hartog, 2000; and le Grand et al., 2004, for studies of overeducation in the labor market).

The central hypothesis I wish to test is whether the jobs women work in a segregated labor market are not compatible with acquiring the skills that are rewarded by the new economy. I call this a "job position" difference across genders. This could arise within the Lazear (2003) framework either because the firms/industries/occupations women work in do not value (weight) such competencies as highly as those that men work in, or that men's jobs are characterized by higher (exogenous) separation probabilities leading them to invest more in generic skills which are easily transferable across to other settings. In fact, if women typically work in extremely thin markets, such as the monopsonistic public sector characterized by a low separation probability, Lazear's model would imply that they would invest in a skill profile that is purely firm-idiosyncratic. Alternatively, if job differences turn up as being important for explaining gender differences in competencies, this would be consistent with a skill-mismatch view of the labor market, whereby for reasons unrelated to skill-biased technological change, for example women's lower geographic mobility, women are not in the jobs which match their competences, but men are.

4. Empirical method

To operationalize the theoretical considerations above, I allow competence acquisition (*C*) to be a function of individual background characteristics such as gender (*G*), age, education, tenure and hours of work (*X*), and the individual's job position (*JP*) as captured by sector (public or private), occupation, industry, number of subordinates, and region indicators controlling for exogenous demand shocks, and firm-specific factors such as firm size. In addition, I include a proxy for generic ability (*A*), thus leading to the specification.

$$C_i = \alpha_0 + \alpha_1 G_i + \alpha_2 X_i + \alpha_3 JP_i + \alpha_4 A_i + \varepsilon_i \qquad (1)$$

If women lag behind men in acquiring new competencies then this will be reflected in a positive coefficient to the gender dummy (male) as competence factor scores increase with increasing competency. On the other hand, if gender differences in competencies are due more to differences in women's job position in a horizontally and vertically segregated labor market, if, as a result of either sorting on preferences or constrained access to certain jobs, women tend to be located in the sectors, industries, occupations, and workplaces which are not compatible with generic skill acquisition, then I expect the gender dummy to lose significance once sector, number of subordinates, firm size, occupational, industrial structure etc. are controlled for. Further, there could be differences in education and work experience (tenure and hours of work) across gender also influencing the rate of skill acquisition. A separate equation is estimated for each of the eight different competencies.

To investigate the wage returns to investing in skill acquisition, I also estimate log "wage" regressions, controlling for standard human capital accumulation as well as new competencies and other work-related factors affecting wages, including current job tenure[3]

$$\ln W_i = \beta_0 + \beta_1 X_i + \beta_2 C_i + \beta_4 JP_i + \nu_i \qquad (2)$$

[3] By "wage" I mean the midpoint of the annual income category for the individual worker, standardized by weekly hours times 47 weeks. Similar wage approximations have been used, e.g., by DiNardo and Pischke (1997) and Entorf and Kramerz (1997).

Each of the competencies is entered individually in the wage regression as they are somewhat correlated (see Appendix C for the correlation matrix).

To the extent that skill acquisition is the outcome of individual investment decisions, whereas the wage equation reflects the demand for labor (marginal product), the two equations can be considered a system of simultaneous equations. Therefore, I experiment with both OLS and IV versions of the wage model above. In terms of exclusion restrictions in the simultaneous model, traditional skills such as math and literary ability (A), which the data contain proxies for (see Appendix A) and which are considered good measures of underlying ability, are assumed to affect wages only through their effect on general skill acquisition. A great deal of previous educational research supports the validity of this instrument. Duncan (1968) envisioned verbal and quantitative skills as being valuable not just in themselves, but also important for the purpose of facilitating the acquisition of other skills and promoting lifelong learning. Bishop (1995) argued even more strongly that productivity at work derives mainly from social skills, good work habits and the ability to work alongside other people, as well as certain job and occupation-specific skills, and not from literary or mathematics skills. These hypotheses have been empirically tested by Heijke et al. (2003), who find in an analysis of the wage payoff to various types of human capital competences in a sample of higher education graduates from eleven European countries that general academic skills do not produce a wage pay-off but play instead a supportive role in the acquisition of management competencies. Drawing on the insights obtained from these studies, math and literary skills are proposed as instruments for the more general kinds of skill acquisition which I consider in specification (1). The IV model is estimated using 2SLS methods.

5. Data descriptives

To begin with, Table 1 shows the raw differences in competencies by gender, after using factor analysis to reduce the data to the eight core competencies. I compare gender differences in the mean factor scores for each skill measure.

Table 1. Gender difference in raw scores on competencies

	Difference in Means (F-M)	P-value
Communication	0.09 (0.03)	0.01
Innovation	-0.11 (0.05)	0.03
Computer	-0.06 (0.04)	0.10
English Language	-0.15 (0.03)	0.00
Training	0.05 (0.05)	0.25
Learning	-0.06 (0.03)	0.08
Mobility	0.04 (0.06)	0.48
Self-Management	-0.11 (0.03)	0.00

Significant gender differences are present, with women possessing greater competency or holding jobs that require more competency than men in Communication, but less in Innovation, English Language, Learning, and Self-Management. There is no significant gender difference in Computer, Training or Mobility competencies.

These raw differences to some extent concur with previous findings. For example, experimental investigations within cognitive and social psychology indicate that women may have superior communicative and collaborative skills compared to men (Hannah and Murachver, 1999; Underwood et al., 1990, 1994). Also, as female workers tend to be one of the groups that has experienced the most rapid rise in computerization (Autor, Katz and Krueger, 1998; Black and Spitz-Oener, 2006), largely because of the nature of their job tasks (clerical, administrative support), it is not surprising that women have the same computer competence as men in these data, as well. Williams (2006), comparing across countries in the ECHP data, finds that Denmark is one of the European countries with the highest proportion of English speakers (70 percent) and that English the most common second language at work. However, 37.6 percent of men use it at work, compared to 30 percent of women. A significant gender gap in English language competency is found in the present sample, as well.

Previous research tends to show that men are employed in jobs which offer more training and use more capital than women (Barron et al., 1993), and that men are more mobile than women in terms of across-firm job changes (Loprest, 1992). The lack of gender differences in training and mobility competencies in my data may reflect the fact that women score relatively high on these competencies because the survey questions do not distinguish between training replenishing skills lost during time away from the labor market and training teaching new skills and job tasks. Further, mobility competence pools together both across-firm moves and within-firm job changes (there are simply too few job changes across firms in our data to allow splitting this competence into within and across-firm mobility). Men also score higher on Innovation, Learning and Self-Management competencies, and these and the other gaps in the data may reflect job differences across the genders, which I will try to control for in the next section.

Figures A1-A16 in Appendix D show histograms of standardized (mean 0, variance 1) competence factor scores separately by gender, along with the non-parametric (kernel) density estimate and a standard normal based on the sample standard error.[4] Despite the differences at the mean noted above, the distributions of competence scores appear remarkably similar across men and women. Still, formal Kolmogorov-Smirnoff tests of distributional equality reveal a significant difference at the 5 percent level in the case of Communication, Innovation, English Language and Self-Management and at the 10 percent level for Learning, and no difference in the case of Computer, Training and Mobility, consistent with the mean differences in Table 1.[5] Note that this similarity in patterns of differences across comparisons of means and distributions is not automatic, since distributions of standardized factor scores are considered.

Means of other background variables are presented in Appendix B. To summarize, women earn significantly lower wages (the raw wage gap is 14.8 percent), have about the same age distribution, and are less likely to have only completed basic or vocational education. Women

[4] The kernel density is estimated using a normal or Gaussian kernel K, such that $\int_{-\infty}^{\infty} K(z)dz = 1$, and with smoothing parameter $h = 1.06\hat{\sigma}_x / T^{0.2}$.

[5] *P*-values are Communication (0.000), Innovation (0.041), English (0.000), Computer (0.256), Training (0.680), Learning (0.104), Mobility (0.931) and Self-Management (0.000).

are more likely than men to hold a medium-cycle degree, are considerably more likely to work in the public sector, in clerical occupations or as assisting spouses, and less likely to work in blue collar (skilled or unskilled) or management occupations. Women also work in smaller firms than men, have lower weekly hours and fewer subordinates, but approximately the same tenure.

6. Estimation results

The evidence above shows significant gender gaps in new skill acquisition. To what extent are these differences driven by gender differences in the level of education, experience, job position in the labor market or ability? Table 2 shows the estimated coefficient α_1 on the gender (male) dummy G_i in (1) when regressing factor scores of competencies on sets of these determinants, starting with the gender dummy only and successively adding education, age and work experience (X_i in (1)), job position (JP_i) and ability (A_i).

The findings show that job position differences explain men's advantage in English language and computer skills, and partially their greater self-management and learning competencies. When controlling for verbal and math ability in addition, the gender gap in self-management skills disappears, but in the most general specification (iv), men retain their advantage in Innovation and women their advantage in Communication, either due to their innate abilities or the requirements on the job. The adjusted R^2s from the most general specification (iv) show a rather good fit for Communication and Learning, but low explanatory power for Training and Mobility. These results are interesting in their own right and constitute the first stage of the system of equations (1)-(2) described in section 5.

Table 2. Competence regressions, estimated male dummy[a]

	(i) gender only	(ii) + educ, age, experience	(iii) + job position	(iv) + ability	Adj. R^2
Communica-tion	-0.092 (-2.74)	-0.29 (-0.93)	-0.040 (-1.30)	-0.074 (-2.62)	0.49
Innovation	0.106 (2.22)	0.157 (3.32)	0.141 (2.56)	0.124 (2.25)	0.12
Computer	0.061 (1.64)	0.048 (1.29)	-0.048 (-1.20)	-0.065 (-1.63)	0.14
English	0.145 (4.39)	0.152 (4.68)	-0.021 (-0.60)	-0.028 (-0.08)	0.19
Training	-0.054 (-1.16)	-0.043 (-0.92)	-0.036 (-0.67)	-0.039 (-0.73)	0.02
Learning	0.058 (1.75)	0.112 (3.54)	0.059 (1.70)	0.037 (1.09)	0.24
Mobility	-0.043 (-0.71)	-0.028 (-0.45)	-0.022 (-0.031)	-0.04 (-0.57)	0.03
Self-Management	0.106 (3.06)	0.130 (3.79)	0.057 (1.54)	0.031 (0.85)	0.19

Note: [a] Asymptotic *t*-values in parentheses.

Next, I estimate the simultaneous model of skill acquisition and wage determination. First, as benchmark, results from simple OLS wage models with White robust standard errors treating competencies as given in (2) are shown in Table 3. Because I am dealing with eight different competencies, I prefer to pool men and women together and retain a gender dummy for parsimony. For purposes of full differentiation, however, I interact gender with age, education, occupation, sector and the relevant skill measure, resulting in a model containing more than 50 parameters, putting some strain on the data. Considering *t*-values greater than 1.5, therefore, the results show that both men and women obtain the same and significant returns to Communication but only women for their computer skills. Men in addition receive significant returns to English language and self-management competencies, but a significant penalty to training investments. Women also receive penalties for Innovation, Training, Learning and Mobility, but these are insignificant. These findings seem to indicate that men in more cases receive positive returns and women in more cases negative returns to investing in new skill acquisition. Although not reported here, the wage regression displays the standard properties and the other estimated coefficients on age, education, tenure, industry, occupation, region, firm size and number of subordinates all have the expected signs, and the effects are of plausible magnitudes.

Table 3. Returns to competencies by gender[a]

	Women	Men	Adjusted R^2
Communication	0.038 (3.14)	0.038 (3.33)	0.30
Innovation	-0.016 (-1.16)	-0.0004 (-0.03)	0.28
Computer	0.019 (1.72)	0.012 (1.05)	0.30
English Language	0.001 (0.07)	0.028 (2.77)	0.30
Training	-0.015 (-1.22)	-0.028 (-2.17)	0.25
Learning	-0.001 (-0.12)	-0.005 (-0.052)	0.31
Mobility	-0.016 (-0.73)	-0.004 (-0.18)	0.29
Self-Management	0.012 (1.10)	0.029 (2.78)	0.30

Note: [a)] Asymptotic *t*-values in parentheses. Prob > F=0.0000 in all cases.

Next, the effect of competencies on wages is estimated within a simultaneous equation approach to the system (1)-(2) using proc ivreg in STATA. The estimated returns to competency acquisition from the IV regression in Table 4 are in a few cases different from the results in Table 3, but show again that men receive significant returns on Communication and Self-Management competencies, while women obtain significant returns to Innovation and English language skills. While men obtain positive returns to their skill acquisition in all cases, women receive wage penalties in the cases of Communication, Learning, Mobility and Self-management competencies, although these effects are insignificant and only in the last case with a *t*-value close to 1. The estimated coefficients are in most cases larger in the IV model than in Table 3 meaning on the face of it that the OLS results were biased downward, but it could also indicate a low signal/noise ratio. Still, the IV estimates are as significant as those from OLS, and the F-values from the first stage are in general large (> 10), except for Training and Mobility where the instruments are weak. Thus, the results of the Hausman test confirm endogeneity in all cases except

Training and Mobility, where no systematic differences are found between OLS and IV.

Table 4. Returns to Competencies by Gender, IV model[a]

	Women	Men	First-stage F[b]	Hausman test
Communication	-0.121 (-0.84)	0.285 (1.90)	70.67	$\chi^2(2)$=6.52 Prob>χ^2=0.0384
Innovation	0.469 (1.52)	0.010 (0.04)	5.80	$\chi^2(2)$=7.48 Prob>χ^2=0.0238
Computer	0.153 (1.29)	0.160 (1.60)	10.61	$\chi^2(2)$=6.82 Prob>χ^2=0.0330
English Language	0.859 (1.59)	0.093 (0.39)	19.07	$\chi^2(2)$=14.13 Prob>χ^2=0.0009
Training	0.177 (0.98)	0.081 (0.21)	1.94	$\chi^2(2)$=1.70 Prob>χ^2=0.4270
Learning	-0.126 (-0.59)	0.408 (1.61)	24.55	$\chi^2(2)$= 15.97 Prob>χ^2=0.0003
Mobility	-0.949 (-0.42)	1.208 (0.60)	1.64	$\chi^2(2)$=4.14 Prob>χ^2=0.1259
Self-Management	-0.341 (-0.97)	0.430 (2.05)	17.07	$\chi^2(2)$= 11.38 Prob>χ^2 0.0034

Note: [a)]Asymptotic *t*-values in parentheses. [b)] Prob>F=0.0000 in all cases except Mobility.

Both OLS and the valid IV results indicate that, except in the case of computer competence, which both men and women benefit from, women seem to get rewarded for different skills than men. Men appear to be rewarded for competencies that are desirable at managerial levels and transferable across jobs, such as Communication, Learning (i.e. being exposed to new challenges, new technology and new forms of organization), and Self-Management while women are penalized for developing their Self-Management skills and instead are rewarded for competencies that are mainly useful at lower levels and within-job such as Innovation (developing new product ideas and services, new work methods), as well as for written and spoken English skills. Moreover, these differences do not merely reflect the characteristics of the jobs that men and women tend to hold. At the same time, there does appear to be in gender differences in the levels of skill acquisition as well in two cases i.e. Communication and Innovation.

When comparing standardized returns to new skills with the wage return on a traditional (continuous) skill measure such as job tenure, for example, the returns to tenure range from 8 percent-17 percent in the IV specifications, while the Beta coefficients corresponding to the returns to new skills in the IV model are -11 percent(F), 45 percent(M) in Communication, 51 percent(F), 28 percent(M) in Innovation, 21 percent for both men and women in Computer, 109 percent(F), 15 percent (M) in English language, -61 percent(F), 136 percent (M) in Learning and -0.09 percent(F), 45 percent (M) in Self-Management. Thus, a one standard deviation increase leads to considerably larger wage change for a typical new skill than for tenure.

7. Discussion

The results show that men receive positive returns to new skill acquisition in all cases, while women only in half the cases (four out of eight categories). When testing the significance of the *gender differences* in returns, only in two cases do they turn out to be significant in two-sided tests at levels better than 20 percent: Communication (F=1.96, Prob>F=0.16) and Self-Management (F=1.99, Prob>F=0.16). That is, men receive larger wage gains than women in acquiring communication and self-management skills. In this section, I further explore possible explanations of these gender differences.

First, could these differences be due to the self-reported nature of the competence data? This is not very likely, since accounting for the bias towards zero in coefficients due to classical measurement error would not change the conclusion, as it only rescales the effects. Further, the particular measurement error suspected here is not classical but of gender-specific sign. Thus, it is possible that men over-report competencies, while women under-report. In this case, the differences in returns would be even larger than those in Tables 3 and 4, i.e., the estimates are conservative.

Second, could the gender gap in returns reflect a difference in skill quality between men and women, with men acquiring a higher wage-producing quality of skills then women? To test this hypothesis, I compare the wage returns to the two competencies of highly-educated women (university education) to with those of men by interacting women's competence level with education. In both cases, I find that highly-educated women obtain the same returns as men (F=0.06, Prob>F=0.80 in Communication, F=0.06, Prob > F=0.80 in Self-Management), while lower-educated women receive lower returns, but not significantly so, particularly not in Self-Management (F=1.56, Prob>F=0.21, and F=0.57, Prob>F =0.45).

Third, it could be the case that women's family responsibilities prevent them from making fully productive use of their skills. To test this, I compare the returns of women in their pre- and post-childbearing years (40+) to those of men. For communication skills, the evidence does tend to point to younger women's greater childcare responsibilities preventing their skill utilization (for the older women-men difference, F=0.01, Prob>F=0.91, and for the younger women-men difference, F=1.54, Prob>F=0.21). On the other hand, younger women seem to receive the same returns to Self-Management as men (F=0.07, Prob>F=0.79), while the older women receive lower returns (F=2.19, Prob>F=0.14). Of course, age group differences could also reflect cohort differences in women's quality of skill acquisition.

Another factor that has been pointed to is women's poorer negotiation skills. To test this explanation, I compare the wage returns of women recently elected to positions of trust within the firm or community and women not elected to such positions with those of men. I find that elected women get the same return to communication skills as men (F=0.49, Prob>F=0.48), while women not in such positions get returns that are significantly lower at 20 percent (F=1.92, Prob>F=0.17). However, the returns to Self-Management are nonetheless similar for the two groups of women, and in both cases lower than for men (F=1.27, Prob>F=0.26, F=1.36, Prob>F=0.24).

Yet another argument for women's lower returns to such competencies could be a mismatch between their acquired skills and the required qualifications of the job. That is, men are better matched to their jobs skills-wise, while women end up in jobs for which they are overqualified, thus not receiving adequate compensation for their skill acquisition. This could plausibly arise if women tend to be more geographically constrained and make their career choices conditionally on their spouse's career choice. Comparing the returns of married versus unmarried women to men, to try to capture the effect of this sort of differential over-qualification as a result of constrained mobility due to marriage, I find in the case of communication skills that unmarried women get the same returns as men (F=0.02, Prob>F=0.88), while the difference between men and married women is statistically larger (F=0.9, Prob>F=0.34). In terms of Self-Management, however, both married and unmarried women get lower returns than men (F=1.52, Prob>F=0.22) and (F=0.78, Prob>F=0.38).

While the evidence in this section points to the importance of skill quality differences, childcare responsibilities, skill-mismatch and negotiation style differences in understanding gender gaps in returns to skill acquisition, it also shows that in the area of Self-Management, men appear to be earning excess returns which cannot be explained away.

8. Conclusions

Whereas the old economy rewarded formal qualifications pertaining to traditional skills such as literacy and numeracy as well as seniority within the organization, the diffusion of new technologies and rapid organizational restructuring has led to demands for strong communication powers, leadership abilities, teamwork and problem-solving skills, computer proficiency, and lifelong learning. These new skills generate considerably higher wage returns than, for example, job tenure. Yet, the available evidence suggests that a large fraction of the workforce, particularly women and minorities, may be trailing behind in acquiring such skills and capturing the employment and wage gains associated with them. I use a unique Danish representative survey, the National Competence Accounts (NKR) 2004, to explore whether, first, there exist significant gender gaps in the levels of new skills and competencies, second, whether these gaps can be explained by women's job position, and third, whether men and women receive the same wage returns to investing in skill acquisition.

While the raw data show significant gaps in competence acquisition, many of these gaps are linked to women's job position in a vertically and horizontally segregated labor market which is not compatible with skill acquisition. Thus, men tend to work in the private sector, in larger organizations, and to have more subordinates, all of which either encourage skill formation or, according to an alternative interpretation, allow for a better match between worker competences and required skills. Controlling for the endogeneity of competencies in a wage regression, I find that there are few significant gender gaps in the levels of competencies, but that men to a larger extent capture the wage gains associated with skill acquisition. In addition, men appear to be rewarded for competencies desirable at managerial levels and more easily transferable across-jobs, such as self-management, command over new technology and communication skills, while women are penalized for acquiring some of the same skills, and are rewarded instead for competencies that are more job-specific in nature and fit better at lower levels, such as making workplace innovations and developing their English language skills. Exploring further the reasons behind these differences, there is some support for quality differences in skills by gender, women's greater family responsibilities, skill mismatch and bargaining style differences as partial explanations for these findings. In the sphere of self-management, however, men appear to enjoy returns in excess of women which are hard to explain away. One interpretation could be that employers in the new economy perceive men as being more naturally suited for leadership roles within the organization, thereby reinforcing gender inequalities along the job hierarchy.

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Appendix A. Factor analysis

Here, I list the variables utilized in constructing core competencies through factor analysis. Principal-component factor analysis was employed (unrotated, standardized factor scores with mean 0, variance 1). In all cases, only the first component had an eigenvalue > 1. As far as possible, I followed the suggested guidelines in a validation report of usable indicators in the NKR data prepared for the Education Ministry by Mandat Analyse (2005)[6]

Communication Competence—is a single component combining:

- Forms of communication (how often do you do the following in connection with your work: write letters/email? talk on the telephone? search for information on the Internet?)
- Communication competence at work (how often do you hold oral presentations, or give instructions or presentations for a group? how often does your job require you to take a stand on issues or problems that others orally communicate to you? to take a stand on issues or problems that others communicate in writing?)
- Information sharing (how often do you and your colleagues share experiences relating to work with each other? to what degree do you and your colleagues discuss ways to make improvements in the way you work?).
  Factor loadings: 0.79592, 0.85992, 0.59439

Innovation Competence—is a single component combining:

- Creative or innovative contributions (to what degree have you, within the last 3 months, either alone or along with others, developed new products or services? to what degree do you think up ideas which can be applied at work in your free time? to what degree, have you, within the last 3 months, participated in trying out new work methods?)
- Conditions for innovative thinking (to what degree is your workplace influenced by new ideas? to what degree are your new ideas supported by your immediate supervisor? to what degree is your ability to develop new ideas an important reason for getting your

[6] Validering og Analyse af det Nationale Kompetence Regnskab, Mandat Analyse (2005).

current job? does your job require you to come up with new ideas?)
- Learned innovative thinking (to what degree have you learned innovative thinking through your education? to what degree have you learned innovative thinking through your post-schooling training?)
  Factor Loadings: 0.79804, 0.80366, 0.62952

Computer Competence—is a single component combining:
- Computer use (how often are you required to use computers as part of your work?
- Computer skills (how good or bad are your computer skills in relation to the requirements of the job?)
  Factor loadings: 0.77714 each

English Language Competence—is a single component combining:
- Spoken English use (how often do you speak English on the job?
- Written English use (how often do you write in English on the job?)
  Factor loadings: 0.93303 each

Training Competence—is a single component combining:
- Training experience (how many days of post-educational training have you obtained in the past 12 months?)
- New skills (has your training led to new job tasks?)
- Productivity (has your training led to greater productivity?)
  Factor loadings: 0.77309, 0.67933, 0.59697

Learning Competence—is a single component combining:
- Learning on the job (within the last 12 months have you experienced new challenges at work?)
- New forms of work organizations (within the last 12 months have you participated in new work teams or groups?)
- More responsibility (within the last 12 months have you been given more or less responsibility?)
- Cooperation (within the last 12 months have you been asked to cooperate with more/fewer persons?)

- New technology (within the last 12 months have you worked with new technology?)
  Factor Loadings: 0.73301, 0.65989, 0.58619, 0.59905, 0.51762

Mobility Competence—is a single component combining:
- Mobility across job functions (have you within the last 12 months changed job function within the same workplace?)
- Mobility across firms (have you within the last 12 months changed workplace for the purposes of learning something new?)
- Mobility across jobs (have you within the last 12 months changed job at the same workplace in order to learn something new?)
- Job rotation (within the last 12 months have you participated in job rotation, exchange of job functions etc. which required learning new things?)
  Factor Loadings: 0.80932, 0.22863, 0.75471, 0.57603

Self-Management Competence—is a single component combining:
- Control over one's workday (to what degree do you plan your own workday?)
- Control over work tasks (to what degree do you yourself decide how to execute your job tasks? to what degree do you have influence in designing your own job tasks? to what degree have you, within the last 3 months, extended your workday because your work required it?)
- Self-management motivation (to what degree do you want to have influence over decision-making at the workplace? to what degree are you well informed about the firm/organization's goals and strategies? to what degree do you feel responsible for the success of the firm/organization? to what degree do you identify yourself with the profile the firm/organization presents to the outside world?)
- Work-life balance (to what degree are you satisfied with the balance between work-life and private life?)
  Factor Loadings: 0.84067, 0.86930, 0.35511

Instruments

Math Ability—is a single component combining:

- Math use (how often do you use mathematics or work with numbers in your day to day work?
- Math ability (how easy or difficult is it for you to apply the mathematics that is required by your work?)
  Factor loadings 0.66523 each

Literary Ability—is a single component combining:

- Reading use (how often do you need to read as a part of your job?)
- Reading ability (how easy or difficult is it for you to do the reading required by your work?)
  Factor loadings 0.70632 each.

Appendix B. Means of background variables

Variable	Description	Mean-Women	Mean-Men
(Log)Hourly Income*	**Log (annual inc. in DKK/wkly. hrs x 47)** [1]	**4.89 (0.46)**	**5.05 (0.46)**
Individual Characteristics			
Age 20-29	=1 if age group is 20-29	0.13 (0.33)	0.13 (0.34)
Age 30-39	=1 if age group is 30-39	0.29 (0.45)	0.29 (0.45)
Age 40-49	=1 if age group is 40-49	0.29 (0.46)	0.28 (0.45)
Age 50-60	=1 if age group is 50-60	0.26 (0.44)	0.25 (0.44)
Basic School*	=1 if highest education is elementary	0.12 (0.32)	0.15 (0.36)
High School	=1 if highest education is high school	0.08 (0.27)	0.07 (0.26)
Vocational*	=1 if highest education is vocational	0.39 (0.49)	0.46 (0.50)
Short-cycle	=1 if highest education is short-cycle	0.07 (0.26)	0.06 (0.24)
Medium-cycle*	=1 if highest education is medium-cycle	0.26 (0.44)	0.14 (0.35)
Tenure	Tenure in years	8.31 (7.07)	8.61 (7.21)
Working hours*	Weekly hours of work	35.71 (6.00)	40.23 (5.75)

Appendix B. continued….

Variable	Description	Mean-Women	Mean-Men
Job Position			
Public Sector*	=1 if employed in public sector	0.53 (0.50)	0.25 (0.44)
Skilled*	=1 if skilled occupation	0.09 (0.29)	0.23 (0.42)
Unskilled*	=1 if unskilled occupation	0.12 (0.32)	0.16 (0.37)
White collar*	=1 if white collar occupation	0.66 (0.47)	0.43 (0.50)
Management*	=1 if managerial occupation	0.06 (0.24)	0.12 (0.32)
Assisting spouse*	=1 if assisting spouse	0.01 (0.07)	0.00 (0.03)
Firm size*	No. of employees	111.99 (153.03)	128.44 (161.63)
Subordinates*	No. of subordinates	2.23 (7.49)	4.19 (10.63)
N		1,790	1,826

Notes: Means of 14 industry categories and 14 region indicators suppressed. 'Midpoint of category. *Significant gender difference. Reference age is > 60 (3.9 percent), reference education is long tertiary (9.1 percent), Reference occupation other work (1.25 percent).

Appendix C. Correlation matrix of competencies

	Comm	Innov	Comp	Engl	Train	Learn	Mobl	Self-Mngmt
Comm	1.0000							
Innov	0.3064	1.0000						
Comp	0.3110	0.0644	1.0000					
Engl	0.1989	0.0675	0.1533	1.0000				
Train	0.1151	0.2109	0.0672	-0.0114	1.0000			
Learn	0.2742	0.2366	0.1671	0.1531	0.2488	1.0000		
Mobl	0.0539	0.0804	-0.0214	0.0072	0.1239	0.2467	1.0000	
Self-Mngmt	0.2713	0.4211	0.1520	-0.0072	0.1312	0.1000	0.0015	1.0000

Appendix D. Figures

Figure A1. Distribution of communication competence—women

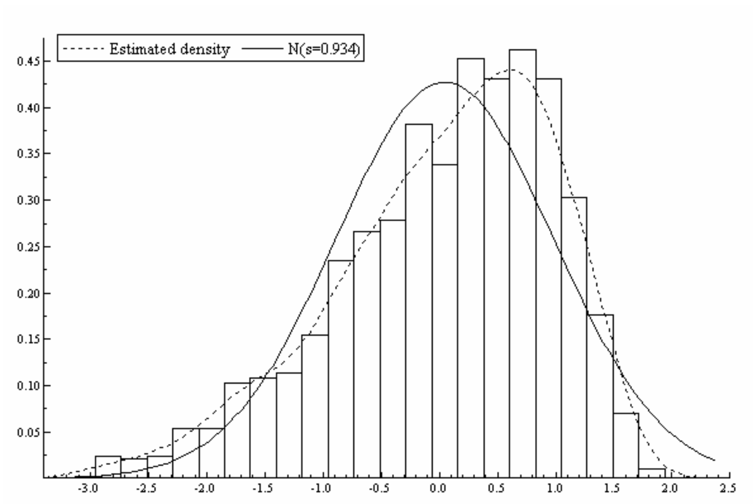

Figure A2. Distribution of communication competence—men

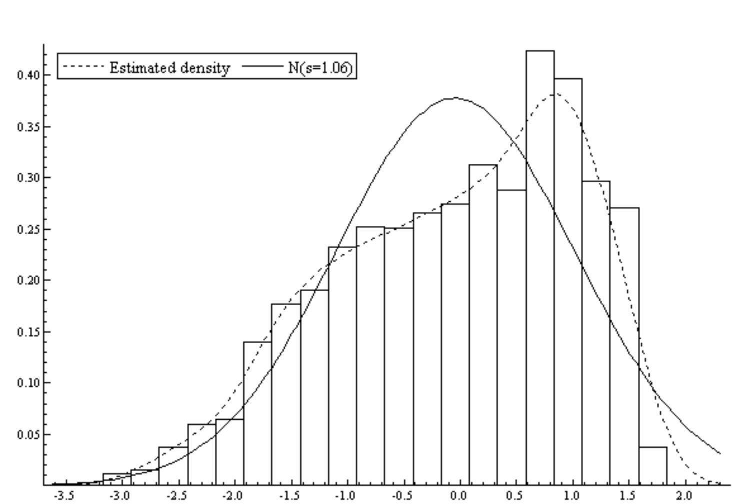

Figure A3. Distribution of innovation competence—women

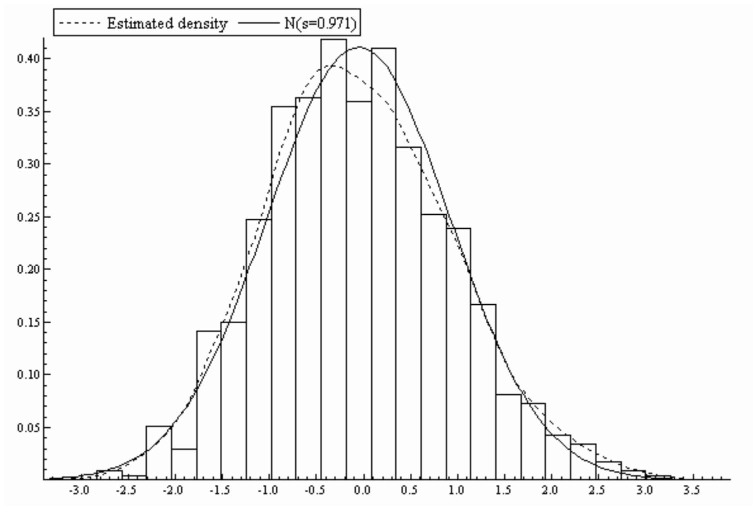

Figure A4. Distribution of innovation competence—men

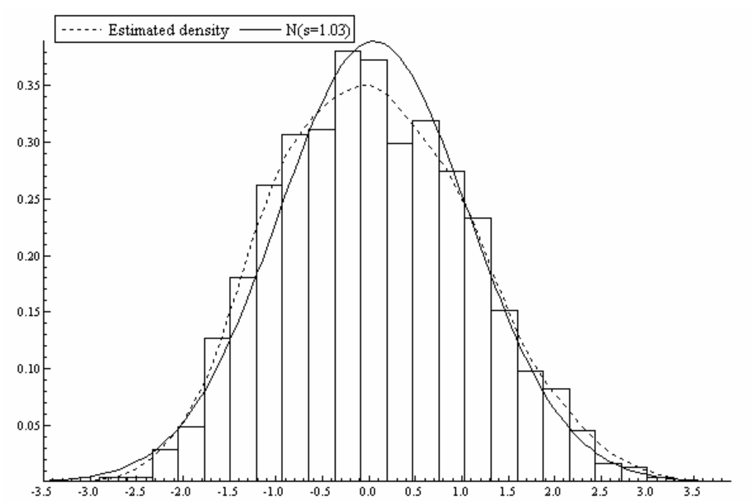

Figure A5. Distribution of computer competence—women

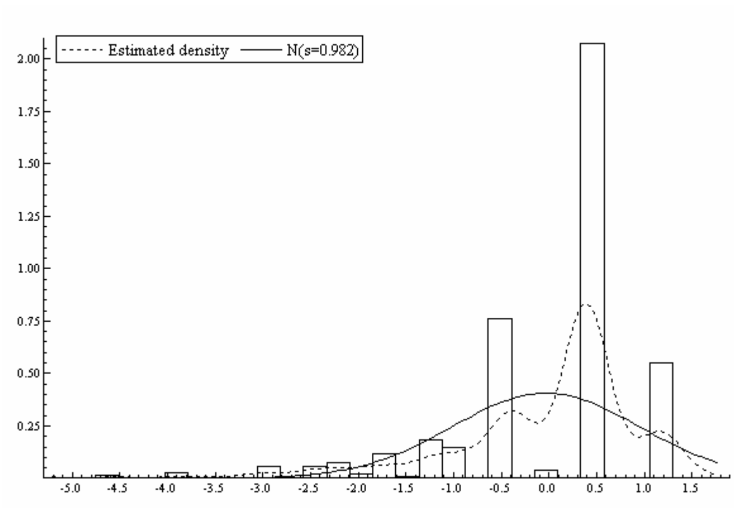

Figure A6. Distribution of computer competence—men

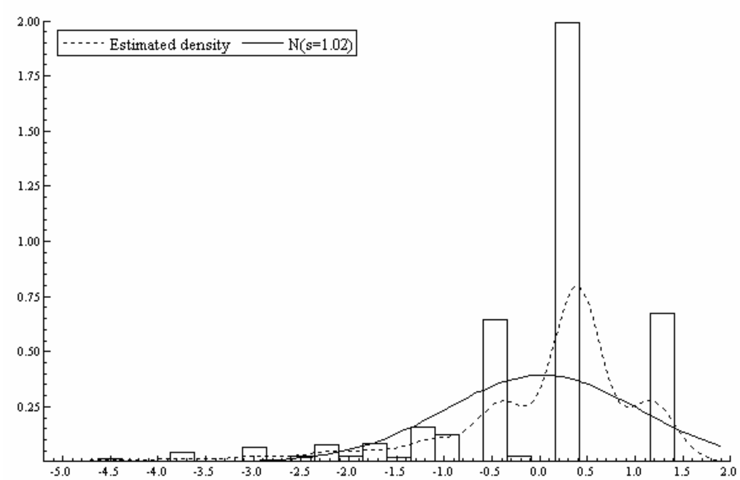

Figure A7. Distribution of English competence—women

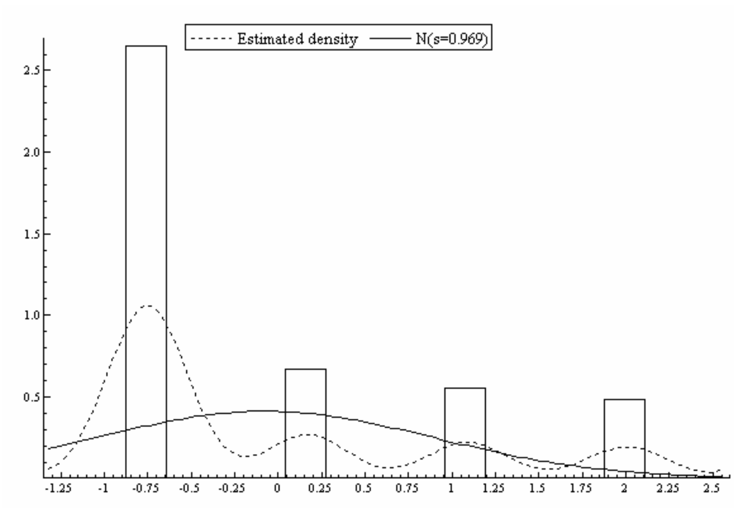

Figure A8. Distribution of English competence—men

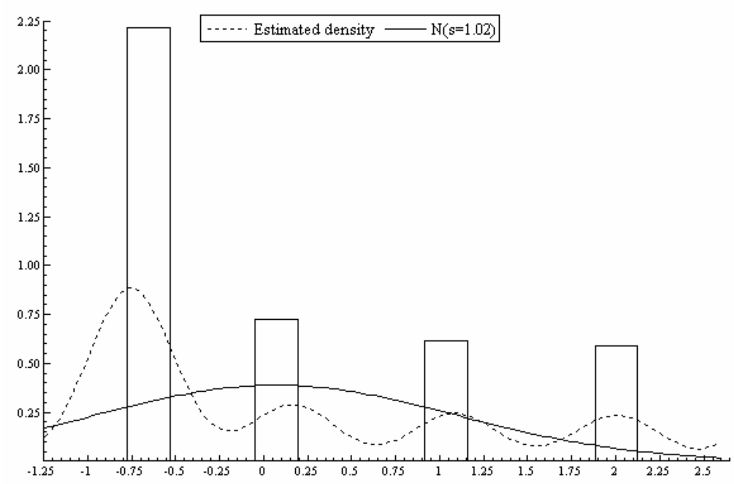

Figure A9. Distribution of training competence—women

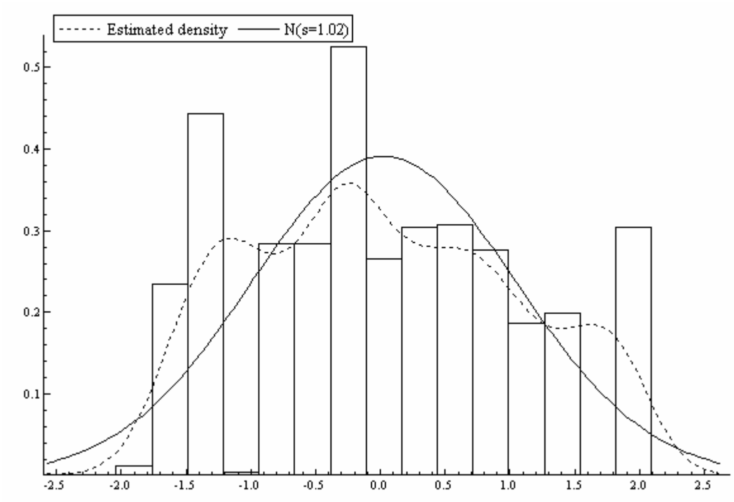

Figure A10. Distribution of training competence—men

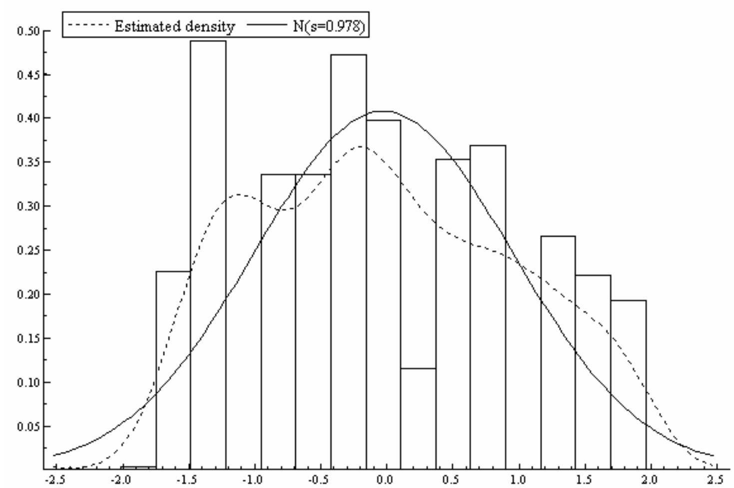

Figure A11. Distribution of learning competence—women

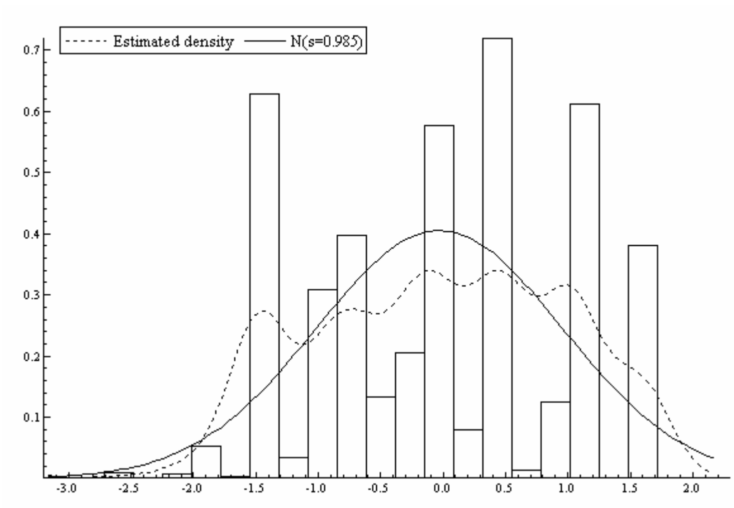

Figure A12. Distribution of learning competence—men

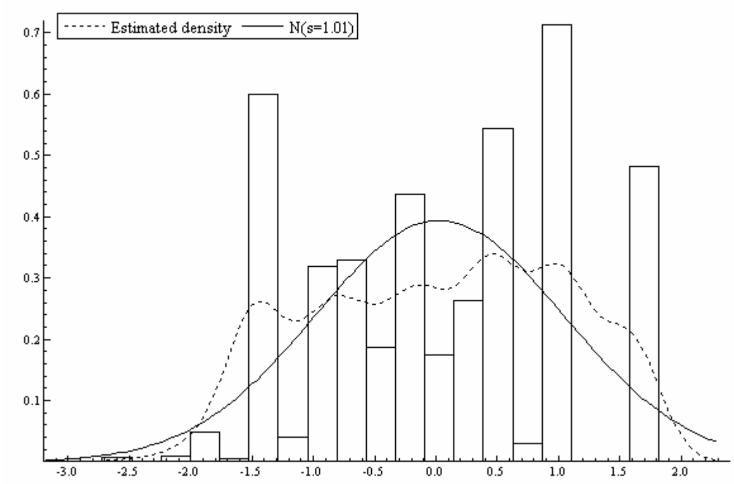

Figure A13. Distribution of mobility competence—women

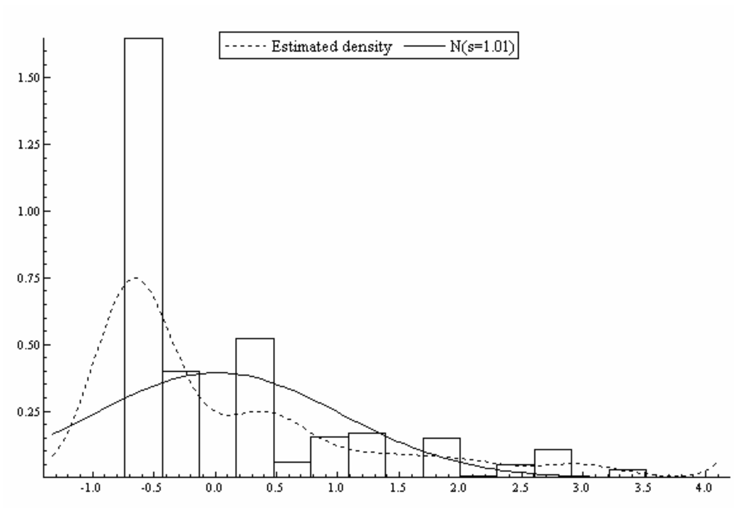

Figure A14. Distribution of mobility competence—men

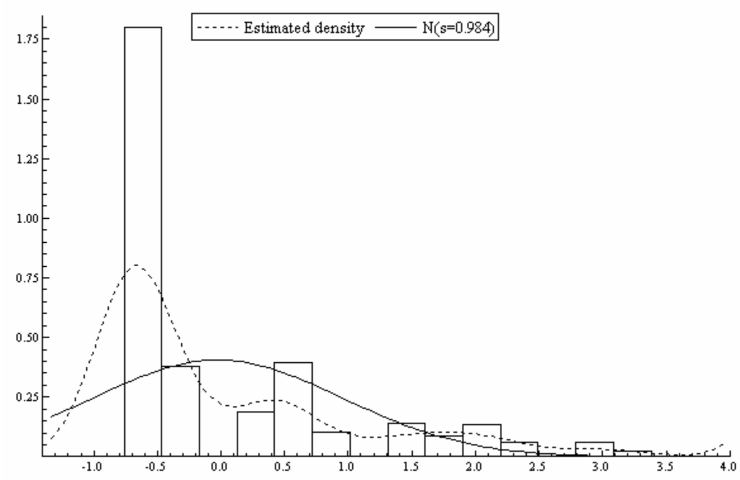

Figure A15. Distribution of self-management competence—women

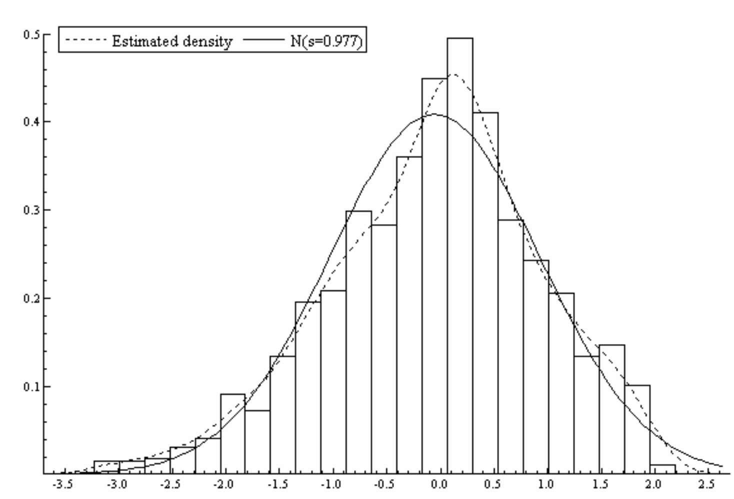

Figure A16. Distribution of self-management competence—men