Education-Occupation Mismatch: Is there an Income Penalty?

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Abstract

This paper adds to the small literature on the consequences of education-occupation mismatches. It examines the income penalty for field of education – occupation mismatches for men and women with higher education in Sweden and reveals that the penalty for such mismatches is large for both men and women. In fact, it is substantially larger than has been found for the US. Controlling for cognitive ability further establishes that the income penalty is not caused by a sorting by ability, at least for Swedish men. The income penalty for men decreases with work experience which is an indication that education-specific skills and work experience are substitutes to some extent. There is no evidence, though, that the mismatched individuals move to a matching occupation over time. Thus, for some, the income penalty seems to be permanent.

JEL classification: I21, J24, J31

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1. Introduction

There is now a fairly large literature on the relationship between overeducation/undereducation (i.e. having a higher/lower education level than that required for the job) and earnings (see e.g. Bourdet & Persson, 2008; Dolton & Vignoles, 2000; Hartog, 2000; McGuinness, 2006; Rubb, 2003; Sloane, Battu & Seaman, 1999). The survey by Hartog (2000) concludes that the return to overeducation is about half to two-thirds of the return to required schooling. The penalty for undereducation is somewhat smaller.[1]

As far as we know, very few studies as yet focus on the mismatch between the individual's field of education and his/her occupation. Still, to fully utilize the stock of human capital in the population it is essential to match individuals' education-specific skills (as opposed to more general skills) with the occupational job characteristics. The pioneering paper by Robst (2007a) emphatically brings out that this is another type of educational matching problem that should be investigated.[2] Using data on US college graduates he finds that having a major subject that does not match one's work is associated with a roughly 11 percent lower annual income compared to having a major subject that does. Thus, the income penalty for a field of education - occupation mismatch seems to be larger than the penalty for being overeducated/undereducated.[3]

Two data-related aspects might affect the interpretation of Robst's results. Failing to control for ability and using a self-reported match/mismatch measure make it hard to infer that it is the mismatch that actually causes the income penalty. A mismatch may well be caused by a sorting by ability, or a self-reported mismatch might be endogenous and related to the wage, i.e. a self-reported mismatch may be a form of rationalization of a general feeling of disappointment with the wage and/or the workplace. Studies show that the method used to measure overeducation/undereducation affects the results (Battu, Belfield & Sloane, 1999; Groot & Maassen van der Brink, 2000). For example, Groot & Maassen van der Brink (2000) find that overeducation is more frequent when a self-reported rather than an objective measure is used.

[1] Recent Swedish studies provide similar results (see Korpi & Tåhlin, 2006; Johansson & Katz, 2007).
[2] In a subsequent paper Robst extends his analysis to cover both types of educational mismatches simultaneously. See Robst (2008).
[3] If the income penalty for one year of overeducation amounts to around 3 percent, then having a job that does not match one's education is comparable to having about four years of overeducation.

Ability seems to be related to being overeducated/undereducated. Sloane, Battu & Seaman (1999) note that promotion and supervisory experience is least common among the overeducated and most common among the undereducated, which suggests that the overeducated might have a lower ability level, and the undereducated a higher ability level, than the correctly matched individuals. They also show that the overeducated have more unemployment spells and involuntary quits than others.

With an impressive dataset covering the entire age-group 28-39 in Sweden, this paper reexamines the field of education - occupation mismatch. The data includes a cognitive test score[4] and detailed education and occupation classifications make it possible to objectively decide whether there is a match or a mismatch. Unlike Robst's study, which is restricted to graduates, our study includes everyone with some university/college education.

The system of higher education in Sweden differs substantially relative to many other countries (for example the US) in that most fields of higher education are very specialized. Hence, the penalty for a field of education - occupation mismatch may be particularly large in Sweden (and in other countries with relatively specialized fields of higher education) since the students learn occupation-specific skills to a larger extent and relatively less of general skills at university/college.

Overeducated individuals seem to have less experience, tenure and training than the correctly matched individuals, which indicates a possible substitution between formal education and experience (Sloane, Battu & Seaman, 1999). Workers outside their field of education also seem to receive more training than other workers (van Smoorenburg & van der Velden, 2000). Since we do not have access to data on work experience and training we are unable to ascertain whether the two types of skills are substitutes or complements. As an alternative we compare the return to (potential) experience between those who work in an occupation that matches their field of education and those for whom there is a mismatch. If the mismatched individuals lack education-specific skills, and these skills are substitutes for the skills learned at the workplace, the income penalty may be expected to decrease with work experience and on-the-job training.

[4] The Swedish military enlistment test.

2. Data

The data is cross-sectional and comprises all individuals in the age-group 28-39 living in Sweden in 2003. Statistics Sweden (SCB) has constructed the data by adding education and income variables from the Swedish Register of Education (UREG) and the National Tax Board to the register of the total population (RTB). Enlistment data from Pliktverket, providing us with the cognitive military enlistment test, is also merged with the dataset.

Only Swedish-born individuals with Swedish-born parents are included in our sample. Excluding individuals with a foreign background[5] ensures that labor market discrimination of such individuals does not affect the results. With this restriction the sample consists of 549 434 men and 518 968 women.

Since the aim is to examine the field of education - occupation matches only individuals with a higher education, i.e. more than twelve years of schooling, are included in the sample.[6] For the age-cohorts in this study the college and university educated consist of 155 767 men and 208 616 women, i.e. roughly one third of the total cohorts. As some fields of education (e.g. in the humanities and languages) are either vague or cannot easily be matched with any specific occupation, we are forced to restrict the fields of education to the more well-defined ones. In so doing, we lose another 36 percent of the individuals and the sample then becomes 97 296 men and 134 813 women.

Excluding 11 percent of the individuals because of missing occupation data (probably caused by non-employment)[7], and 3 percent for whom the annual income from work is zero, makes the final sample 80 368 men and 119 265 women. Together, these exclusions incur the risk that the final sample is not perfectly representative of the total (non-foreign background) population of university/college educated. Rather, our study reports the income penalty for mismatches in the (non-foreign background) population of (employed) individuals who have invested in any of the more common or well-defined Swedish fields of higher education.

[5] That is both the first and the second generation of immigrants.

[6] Ph.D.s and those who have attended “komvux” (a supplementary adult upper-secondary education) are also excluded.

[7] In addition certain types of occupations (heads and managers, politicians, sportsmen and models) that cannot be matched with a field of education are also excluded.

An alternative to using positive income as a cut-off for our income variable would be to use annual income (from work) above a certain level. That would (at least to some extent) eliminate that part of the mismatch penalty that could reflect e.g. involuntary part-time work. But to get results that are comparable to those in Robst's study (which uses the log of annual wages) and to the overeducation/undereducation literature we start out by using positive income as our cut-off. In a sensitivity analysis we then study whether the choice of cut-off affects the results.

Our educational attainment measure, SUN2000, is for the year 2003 and describes both the highest level of education achieved and the field of education. Twenty-four different fields of education are constructed on the basis of this information.[8]

Most fields of education (included in our final sample) are precise and match one distinct occupation perfectly, whereas some fields of education are broader and match two occupations (e.g. the social science field). All these field of education-occupation combinations are classified as being matched. Many fields of education also weakly match with one or more occupations; these combinations are classified as weakly matched. The remaining field of education-occupation combinations are then classified as mismatched.[9] Measurement errors[10] in the matching are likely to result in a downward bias in the mismatch effect, which means that the estimated mismatch effect will be a lower bound of the income penalty.

(Table 1 about here)

Table 1 lists the fields of education together with the number of individuals within each field of education, the share of individuals with a job that does not match his/her field of education (mismatch), and the share with a job that weakly matches his/her field of education (weak match). 23 percent of the men and 19 percent of the women are mismatched and 16 percent of the men and 10 percent of the women are weakly matched.

[8] The SUN2000 measure is a revision of the former SUN classification adjusted to fit the International Standard Classification of Education (ISCED97). The education level is the highest level achieved and field of education is based on the individual's main field of education. The field of education is initially given as a three-digit scale. Our classification into different fields of education is based as often on the second as on the third digit. The fields of education that are most often excluded from the data (for being too vague and/or too hard to match to occupations) are the following: language/arts, health, services and transport. The occupation data are also given as a three-digit scale.

[9] Table A2 reports the matrix of fields of education – occupations matching.

[10] For example, in Sweden there are individuals who invest in an additional field of education (often lawyers). However, there no information regarding multiple degrees or multiple fields of education.

People with dentist, police, law and veterinarian educations are least often mismatched, whereas those with a biology, psychology or artistic education are most often mismatched. It is also interesting to note that for some fields of education there are clear gender gaps in the share mismatched.[11] Men are mismatched to a larger extent than women in some female-dominated fields of education (pre-school teacher, librarian, pharmacist, nurse) whereas women are mismatched to a larger extent than men in some male-dominated fields of education (master of engineering, engineer). Additional descriptive statistics are reported in table 2 for the matched, the weakly matched and the mismatched. Somewhat surprisingly, both age and experience are on average about the same for the matched and mismatched, men as well as women. But it can also be seen that the mismatched men (on average) have a substantially lower income level than the matched men. This is also the case for the mismatched women, although somewhat less pronounced. Weakly matched men have about the same average income level as the matched men and the same goes for the weakly matched women relative to the matched women. The descriptive statistics also reveal that both men and women without a completed degree are overrepresented among the mismatched.

(Table 2 about here; preferably above)

3. Results

3.1 The income penalty for being mismatched or weakly matched

To study the income differences between matched, mismatched and weakly matched individuals regular, Mincer-type income equations are estimated. The full model specification is:

$$\ln y = \alpha + \beta_0 S + \beta_1 Exp + \beta_2 Exp^2 + \beta_3 MM + \beta_4 WM + \delta_j FD_j + \gamma ND + \lambda X + \varepsilon \qquad (1)$$

where the logarithmic of annual income from work is regressed on years of schooling, S, potential experience,[12] Exp, potential experience squared, Exp^2 and individual characteristics X. The income penalty for being mismatched, β_3, and weakly matched, β_4,

[11] The gender differences in the incidence and character of education-job mismatches in the US are studied in-depth in Robst (2007b).

[12] Since the data does not contain actual work experience the standard way of calculating potential experience is used, i.e. exp = age – years of schooling – 7. (Swedish children start school when they are 7 years old).

are picked up from the indicator variables *MM* and *WM*. The dummy variables FD_j indicate field of education and the dummy variable *ND* that the individual does not have a degree.[13]

Table 3 reports, separately for men and women, the income penalty for being mismatched and weakly matched. Column 1 gives the income differences when the education of the individual is described only by the years of schooling variable. Being mismatched is associated with a sizably lower income than being matched, about 38 percent lower for men and about 26 percent lower for women. The weakly matched, on the other hand, have an income that is roughly comparable to that of the correctly matched individuals.

(Table 3 about here)

Controlling for field of education, $FD_{j,}$ with j indicator variables, now β_3 (β_4) gives the income difference between two individuals with the same field of education but one matched and the other mismatched (weakly matched). Column 2 shows that adding the field of education to the specification changes the income penalty for being mismatched in opposite directions for men and women; it decreases to about 34 percent for men and increases to about 32 percent for women. The finding that the gender gap in the income penalty for being mismatched decreases (from 12 percent to 2 percent), when field of education is controlled for, indicates that mismatched men have invested in relatively low-paid fields of education, whereas mismatched women have invested in relatively well-paid fields of education.[14] Given the field of education, being weakly matched is also associated with an income penalty for both men and women, but the penalty is much smaller than for the mismatched individuals.

Since the sample contains individuals who have not finished their university/college education, and thus not achieved a degree, the variable *ND* (No Degree) is included in the model.[15] When this is taken into account (in column 3), the income penalty for being mismatched decreases by about 2 percentage points for men

[13] For a list of variables, see Table A1.

[14] This is probably also related to gender differences in the reasons for being mismatched, see Robst (2007b; 2008). Based on his data Robst is able to distinguish between supply-side reasons (pay and promotion opportunities, job location, family, change in career interests) and demand-side reasons (unable to find a degree-related job) for the individual's decision to accept work outside his/her degree field.

[15] Table 2 reveals that 15 percent of the men and 12 percent of the women in our sample do not have a degree. Among the mismatched the shares are 28 percent respectively 27 percent.

and 4 percentage points for women. Moreover, the income penalty for being weakly matched decreases somewhat. Still, the overall conclusion is that having a degree or not does not explain the income difference between the matched and the mismatched (or weakly matched) individuals. To illuminate this further, we have estimated separate earnings equations for those with and without a degree and found that there are large differences in the mismatch penalty. For those without a degree the income penalty for being mismatched amounts to around 70 percent (for both men and women) whereas it is about 20 percent for men and about 15 percent for women who have a degree.

3.2 Sorting by ability?

As Robst acknowledges, the sorting into matched and mismatched jobs could be a result of ability differences between the individuals. For example, if there is excess supply from certain fields of education it might be the low ability (and low productivity) individuals who have to settle for jobs that do not match their education. The dataset provides us with a cognitive test result for 90 percent of the men. At the age of eighteen all Swedish men take this test when enlisting in the military.[16] When we estimate the effect of being mismatched/weakly matched for this subset of men we find (column 4 in table 3) that the income penalty is as large as in the main sample (column 3), i.e. 32 percent for the mismatched and 7 percent for the weakly matched men. In column 5, when the cognitive test score has been added to the income equation, the income penalty remains unchanged for both the mismatched and the weakly matched men.[17] Hence, we are able to conclude that the result is not driven by a sorting by ability.

3.3 Is work experience a substitute for education-specific skills?

If the mismatch effect varies with potential experience, this might tell us something about what is causing the income penalty, and whether work experience and training are substitutes for education-specific skills.

(Table 4 about here)

[16] Even if enlisting in the military is mandatory in Sweden some people have been exempted from enlisting because of health reasons. For more information about the test, see Nordin (2008).

[17] When using subtests of the enlistment test, which measure different kinds of skills (e.g. verbal, spatial or logical skills), the results also hold.

By interacting the mismatch and the weak match variables with the experience variable we analyze whether the return to experience differs for the three groups.[18] The results are reported in table 4, column (1) for men and column (4) for women. For men, the mismatched individuals have a substantially higher return to experience than the matched individuals. Weakly matched women have a lower return to experience than matched women, but for the mismatched women the return to experience is the same as for the correctly matched women. More detail is provided for men and women in figures 1 and 2 respectively, where the income premia for each year of experience are illustrated separately for each group.[19] For men, figure 1 clearly shows that the negative influence of being mismatched decreases with potential experience. The income penalty is roughly twice as large for those with little experience compared to for those with fifteen to nineteen years of experience. The same clear pattern is not observed in figure 2 for women.[20] Hence, for mismatched men it seems as if investment in work experience partly closes the gap in education–specific skills.

(Figures 1 and 2 about here)

3.4 Same occupation, different fields of education

Controlling for occupation instead of field of education changes the research question somewhat. When using fixed effects to control for occupation the specification gives us the income difference between two individuals who work in the same occupation (and who have the same years of education and degree/no degree) but where one has a

[18] To facilitate the comparison the squared experience variables are excluded. This is done primarily since the linear experience coefficient for women is negative (which does *not* mean that the return to experience generally is negative – see our further analysis of the return to experience reported in Figure 2) which means that the comparing becomes difficult.

[19] Here we estimate a fully flexible model where each year of experience, for each group, is represented by a dummy variable. It should be noted that the method for constructing potential experience implies that the experience estimates at the ends of the experience distribution are based on distinct groups of individuals. For example, the least experienced are all aged 28 and have seventeen years of schooling and the most experienced are all aged 39 and have thirteen years of schooling. This means that the experience estimates will gradually be based on more variation in age and years of schooling when going from the ends of the experience distribution. But as the experience estimates, from 8 to 15 years of experience, are based on all possible number of years of schooling, the variation in age will at its most be five age-groups, implying that the experience estimates will to some extent reflect cohort differences.

[20] The U-shaped pattern probably reflects the period in their life-cycle when high-educated women in Sweden tend to have children, i.e. a couple of years after finishing their higher education.

matching education (or a weakly matching education) and the other does not. According to the results in table 4, column (2) for men and column (5) for women, for individuals working in the same occupation the income is around 13 percent lower (for both men and women) for the mismatched individuals.

3.5 Are the mismatched individuals working less than full-time?

Another factor contributing to the large mismatch effect might be that the mismatched individuals have a weak position in the labor market, and often work part-time or have temporary jobs. Excluding individuals with an annual income below SEK 50 000, i.e. people not working full-time and/or full-year, enables us to analyze whether the mismatch penalty changes. For this restricted sample, column (3) in table 4 for men and column (6) for women report a considerably lower income penalty for the mismatched individuals, 17 percent for men and 12 percent for women, compared to the full sample. This finding reveals that the mismatch penalty, in part, may be associated with having a very low annual income, and probably reflects a weak labor market position. Restricting the sample to those with an annual income above SEK 100 000 lowers the income penalty further, to 9 percent for men and 5 percent for women. Re-estimating the more flexible years of experience model (with interactions, corresponding to columns (1) and (4) in table 4) for the income-restricted samples tends to decrease the differences in return to experience between the matched and the mismatched groups.

That the differences in returns to experience largely disappear when the lowest annual incomes are excluded shows that really low incomes are relatively frequent among the mismatched with low levels of experience. At the same time, though, the share of mismatched individuals is almost constant over the experience distribution (table 2 reports that the mean years of experience are almost the same for the three groups). Together these findings indicate that the mismatched individuals, initially probably working part-time and/or in temporary jobs, with increasing experience tend to get full-time, full-year employment. Still, as the share of mismatched individuals does not change with years of experience, they seem to stay mismatched.

4. Conclusions

The rather specialized university/college education in Sweden probably contributes to the substantial income penalty for working in an occupation that does not match one’s field of education. When comparing two men with the same educational background (same field of education, same years of schooling and having/not having a degree) the mismatched man suffers a 32 percent income penalty. The corresponding income penalty for women is 28 percent.

By controlling for cognitive ability we establish that (at least for men) the income penalty is not caused by a sorting by ability. If the individual chooses field of education based on personal endowments (other than cognitive ability), the income penalty might still depend on a mismatch in personal skills rather than a mismatch in field of education-occupation. But since the income penalty could be wiped out by changing occupation, we argue that it is a true mismatch effect.

Finally, the income penalty decreases with (potential) work experience, particularly for men. The income penalty might therefore, partly, depend on a lack of education-specific skills, and work experience serve as a substitute that closes the skill gap. A plausible explanation for the finding is that attaining necessary skills helps to turn part-time and temporary employment into full-time and permanent employment but there is no evidence that the mismatched individuals move to a matching occupation over time. Thus, for some, the income penalty seems to be permanent. This is also supported by our findings for the restricted income samples. Also for these groups of individuals, likely to be full-time, full-year workers, there is a significant and substantial (even if smaller than for the unrestricted sample) income penalty for being mismatched for both higher-educated men and higher-educated women.

With data available on hourly wage, hours of work, actual work experience and training, these issues should be analyzed more rigorously in the future.

From a theoretical perspective, the existence of human capital mismatch raises some important questions. According to human capital theory a worker is paid his/her marginal product, which is only determined by the human capital of the individual. Wage differences between matched and mismatched workers contradict human capital theory, since they indicate that the marginal product of a worker also depends on his/her occupation/job (see Hartog & Oosterbeek, 1988). Based on evidence from the overeducation literature, McGuinness (2006) relates the findings to assignment models (Sattinger, 1993), in which the assumption is that wages are determined both by the human capital of the worker and by the occupation/job characteristics. Thus, our findings provide additional support for the assignment model.

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Appendix

Table A1. Variable list

Variable:	*Construction of variable*
Logarithmic income	Logarithmic annual income from work above 50 000 SEK.
Schooling (SUN2000)	Years of schooling constructed from the SUN2000 education level measure.
Potential experience	Age-7-Years of schooling.
Field of education	Twenty-four different fields of education constructed from the SUN2000 field of education measure.
Occupation	Thirty-eight different occupations that have been created according to the three-digit scale of SSYK (Standard för svensk yrkesklassificering).
Mismatch	To have a field of education that does not match any occupation.
Weak match	To have a field of education that weakly matches any occupation.
Test Score	The Swedish Enlistment Battery test (ranging from 1 to 9).
No degree	Either 30-119, 120-179 or at least 180 ECTS (European Credit Transfer System) credits but no degree. (60 ECTS credits correspond to one year of full-time studies).
Labor market region	81 labor market regions (Nutek's basis of division).

Table A2. The field of education – occupation matches respectively weak matches.

Field of education / Occupation	Pre-school teacher	Comp. teacher	High school teacher	Theology	Artistic	Journalism	Psychology	Social science	Librarian	Business adm.	Law	Biology
Pre-sch. teacher	19,477	128	95	4	16	9	17	12	4	45	1	3
Comp. teacher	672	12,345	8,224	12	72	34	31	64	13	117	15	71
High sch. teacher	161	281	6,803	16	360	36	8	32	1	93	6	55
Special teacher	496	481	638	10	108	29	23	64	8	188	12	18
Priest	4	6	9	788	8		1	1		2		1
Journalist/artist	43	44	298	18	1,436	1,504	31	326	73	733	66	35
Photographer	4	4	14		123	10	2	2	5	18	2	5
Psychologist	36	5	10	60	5	7	1,003	118		62	26	1
Social scientist	4	3	29	2	18	19	16	93	3	110	10	4
Other high off.	23	14	17	2	6	18	73	221		226	85	2
High adm.	63	51	163	9	88	146	93	1,160	15	1,327	783	218
Librarian	8	7	26	6	79	3	6	62	749	24	7	8
Bus. economist	374	211	467	17	349	514	416	1,607	79	20,424	,090	133
Lawyer		2	2		1	3	2	25		92	3,878	
Biologist	3	4	24			5	2	5		38		205
Biomedicine	1		7		1		2			3		47
Physicist	1	3	8					4		2		62
Mathematician	1	2	3		2	2	2	26		42	4	2
Data processor	71	95	208	3	127	97	55	188	33	2,645	55	27
Engineer	29	33	107	4	103	24	21	38	5	383	8	105
Master of eng.	6	14	63		92	7	19	39	2	395	38	123
Safety inspector	2	2	9	1	3		2	9		46	10	17
Physician etc.	2	3	4	1	1	1	27	2		33	1	17
High nurse		2	30				4	2		11	4	8
Low nurse	2		29	2	3			3	1	3	2	7
Treatment ass.	340	57	125	58	28	10	89	70	1	66	11	6
Attendant	1,104	332	667	41	375	123	293	254	31	655	33	296
Police	11	13	23			3	7	15		24	19	1
Security	35	26	71	4	27	18	33	46	1	126	23	12
Soldier		1	11			1	3	11		32	11	1
Pilot		3	19		1	1		5		19	1	1

Salesman	280	140	274	7	183	81	46	114	8	819	27	38
Services	56	42	83	4	59	22	9	37	5	171	6	31
Office worker	572	283	438	20	335	232	175	544	83	3,664	160	133
Farmer	20	6	32	2	13	2	1	11	1	39		21
Craftsman/const.	59	43	114	5	198	23	17	29	6	215	7	22
Operator/electric.	107	56	147	8	96	34	28	55	9	344	9	24
Other low-qualified	145	86	155	4	101	35	23	65	10	373	10	36

Field of education / *Occupation*	*Physics*	*Math./statistics*	*Comp. science/ informatics*	*Master of eng.*	*Engineer*	*Physician*	*Veterinarian*	*Dentist*	*Pharmacist*	*Nurse*	*Police training*	*Military training*
Pre-sch. teacher	4		18	6	7					11		
Comp. teacher	41	13	63	65	44	7		1		8	3	9
High sch. teacher	24	9	48	38	26	4	3			22		10
Special teacher	11	3	56	41	40	3			1	24	21	46
Priest			3	1						6		
Journalist/artist	18	4	67	80	68	6		1	5	19	2	10
Photographer	5	1	13	26	50	3				1	1	3
Psychologist			2	1	1	1				25	1	4
Social scientist	6	4	9	12	2	2				3		
Other high off.	3	3	31	6	5					19	1	8
High adm.	93	74	132	413	101	4			6	85	37	28
Librarian	3		4	9	6	2				1		
Bus. economist	172	114	964	1,835	847	34	3	4	32	409	55	211
Lawyer			6	22	1				6		1	1
Biologist	47			72	36	8	8		30	27		
Biomedicine	41		4	7	23	28		4	9	119		
Physicist	323		8	352	80	5	1	1	21	10		
Mathematician	3	126	32	86	10				2	1		1
Data processor	157	198	7,204	3,773	1,759	9			2	60	5	101
Engineer	269	29	437	2,877	3,732	8	1		6	12	1	137
Master of eng.	507	63	448	8,895	1,717	12		1	27	23		47
Safety inspector	32	3	16	105	178	2			7	4	2	11
Physician etc.	4	1	2	4	1	4,485	313	612	259	53		2
High nurse	1		3	4		15		4	21	6,439		
Low nurse	4	1	3	2	2	19	1	1	3	14,289		
Treatment ass.	6	1	34	7	9	11				36	1	3
Attendant	130	18	292	140	89	195	5	2	11	683	6	8
Police			8	3	6	1				22	3,320	21
Security	9		75	22	37	8				22	6	14
Soldier	10		18	85	19	6	1			1	3	3,810

Pilot	1	1	7	14	26					1	17	29
Salesman	31	7	254	73	71	17			2	47	3	12
Services	5	3	52	17	11	4				29	1	6
Office worker	101	39	912	283	235	53		2	5	145	13	28
Farmer	4		14	36	16	1	3			10	2	1
Craftsman/const.	16	12	199	75	273	7				15	3	40
Operator/electric.	49	15	326	104	299	12		1		21	3	20
Other low-qualified	22	11	189	61	37	15		1	8	23	3	4

[a]A thick line surrounding the cell indicates a match between the field of education and the occupation. A thin line surrounding the cell indicates a weak match between the field of education and the occupation. The unmarked cells are mismatched combinations.

Tables and figures:

Table 1. The fields of education and the shares of matched, mismatched and weakly matched.

	Men				*Women*			
	Match	*Mismatch*	*Weak match*	*N*	*Match*	*Mismatch*	*Weak match*	*N*
Pre-school teacher	64%	27%	9%	2,291	82%	13%	5%	21,921
Comp. teacher	73%	17%	10%	2,340	85%	10%	5%	12,488
High school teacher	76%	21%	3%	7,222	78%	18%	4%	12,224
Theology	75%	25%	0%	573	67%	33%	0%	535
Artistic	40%	60%	0%	1,962	32%	68%	0%	2455
Journalism	54%	46%	0%	936	47%	53%	0%	2117
Psychol.	39%	61%	0%	739	39%	61%	0%	1841
Social science	24%	33%	43%	2,233	23%	32%	45%	3,126
Librarian	52%	42%	6%	241	69%	23%	8%	905
Business adm.	62%	20%	18%	15,001	60%	19%	21%	18,608
Law	65%	9%	26%	2,891	57%	11%	32%	3,529
Biology	14%	72%	14%	574	10%	69%	21%	1,222
Physics	12%	50%	38%	1,024	16%	41%	43%	1,128
Math. or statistics	13%	31%	56%	499	24%	33%	43%	254
Computer science	64%	31%	5%	7,397	54%	34%	12%	4,556
Master of eng.	60%	18%	22%	14,530	62%	28%	10%	5,122
Engineer	38%	25%	37%	7,754	36%	36%	28%	2,110
Physician	90%	10%	0%	2,385	90%	10%	0%	2,602
Veterin.	91%	9%	0%	55	93%	7%	0%	284
Dentist	96%	4%	0%	198	97%	3%	0%	437
Pharmacist	41%	59%	0%	112	61%	39%	0%	351
Nurse	83%	13%	4%	2,506	92%	5%	3%	20,219
Police training	95%	5%	0%	2,520	94%	6%	0%	991
Military training	83%	17%	0%	4,385	87%	13%	0%	240
Total	61%	23%	16%	80, 368	71%	19%	10%	119, 255

Table 2. Descriptive statistics of the matched, the weakly matched and the mismatched individuals.

Men	*Age*	*Log income*	*Schooling*	*Experience*	*No degree*	*N*
Match	33.38	12.64	15.24	11.14	0.12	49,632
	(3.40)	(0.60)	(0.96)	(3.60)	(0.32)	
Weak match	33.04	12.63	15.18	10.87	0.12	12,498
	(3.35)	(0.69)	(0.91)	(3.5)	(0.33)	
Mismatch	33.32	12.21	14.83	11.49	0.28	18,238
	(3.47)	(1.04)	(1.02)	(3.66)	(0.45)	
Total	33.31	12.54	15.13	11.18	0.15	80,368
	(3.41)	(0.76)	(0.98)	(3.61)	(0.36)	
Women						
Match	33.43	12.00	14.98	11.44	0.072	85,283
	(3.45)	(0.95)	(0.87)	(3.72)	(0.26)	
Weak match	33.20	12.05	14.96	11.24	0.16	11,9
	(3.47)	(0.95)	(0.92)	(3.74)	(0.37)	
Mismatch	33.25	11.72	14.77	11.48	0.27	22,072
	(3.51)	(1.19)	(0.96)	(3.73)	(0.45)	
Total	33.37	11.95	14.94	11.43	0.12	119,255
	(3.47)	(1.00)	(0.90)	(3.73)	(0.32)	

Table 3. OLS income equation estimates.[a]

Men	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Mismatch	-.378 (.006)***	-.340 (.006)***	-.316 (.006)***	-.324 (.007)***	-.320 (.007)***
Weak match	-.005 (.007)***	-.078 (.007)***	-.069 (.007)***	-.070 (.007)***	-.072 (.008)***
Years of Schooling	.133 (.003)***	.137 (.004)***	.057 (.004)***	.063 (.004)***	.056 (.004)***
No degree			-.346 (.008)***	-.339 (.009)***	-.343 (.009)***
Exp	.034 (.005)***	.033 (.004)***	.041 (.004)***	.037 (.005)***	.036 (.005)***
Exp^2	-.000 (.000)	-.000 (.000)	-.001 (.000)***	-.000 (.000)***	-.000 (.000)*
Test Score					.030 (.002)***
Field of education	no	yes	yes	yes	yes
R^2	0,128	0,180	0,197	0,197	0,200
N	80,368	80,368	80,368	71,967	71,967
Women					
Mismatch	-.263 (.007)***	-.318 (.008)***	-.279 (.008)***		
Weak match	.025 (.010)***	-.101 (.010)***	-.087 (.010)***		
Years of Schooling	.214 (.003)***	.174 (.004)***	.091 (.005)***		
No degree			-.386 (.010)***		
Exp	-.084 (.005)***	-.080 (.005)***	-.082 (.005)***		
Exp^2	.005 (.000)***	.005 (.000)***	.005 (.000)***		
Field of education	no	yes	yes		
R^2	0,0616	0,096	0,107		
N	119,265	119,265	119,265		

[a]The dependent variable is logarithmic annual income from work. In all models we control for years of schooling, experience, experience squared, married, and labor market region. In column (2) field of education is added, and in column (3) we also add if the individual does not have a degree. In columns (4) and (5) the sample is restricted to those who have taken the enlistment test. In column (4) it is the same model as in column (3). In column (5) the test score is included in the model specification. Standard errors in parentheses.

Table 4. OLS income equation estimates.[a]

	Men			*Women*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Mismatch	-.536 (.020)***	-.122 (.007)***	-.167 (.004)***	-.303 (.024)***	-.132 (.010)***	-.119 (.004)***
Weak match	-.122 (.022)***	-.014 (.008)***	-.032 (.004)***	.011 (.030)	-.003 (.012)	-.060 (.005)***
Years of Schooling	.061 (.004)***	.039 (.003)***	.041 (.002)***	.086 (.005)***	.057 (.004)***	.049 (.003)***
No degree	-.341 (.008)***	-.284 (.008)***	-.201 (.005)***	-.391 (.010)***	-.299 (.010)***	-.162 (.005)***
Exp	.021 (.001)***	.038 (.004)***	.041 (.003)***	.025 (.001)***	-.085 (.005)***	-.034 (.003)***
Exp^2		-.001 (.000)***	-.001 (.000)***		.005 (.000)***	.002 (.000)***
Exp*mismatch	.019 (.002)***			.003 (.002)		
Exp*weak match	.005 (.002)***			-.009 (.002)***		
Field of education	yes	no	yes	yes	no	yes
Occupation	no	yes	no	no	yes	no
R^2	.198	.254	.276	.104	.137	.178
N	80,368	80,368	77,584	119,265	119,265	106,739

[a]The dependent variable is logarithmic annual income from work. In all models we control for years of schooling, no degree, married, and labor market region. In columns (1) and (3) for men and columns (4) and (6) for women field of education is controlled for. In column (1) for men and column (4) for women interactions between experience and the mismatch and weak match variables are included. In columns (2) and (5) occupation is controlled for. In columns (3) and (6) the sample is restricted to those with an annual income above SEK 50 000. Standard errors in parentheses.

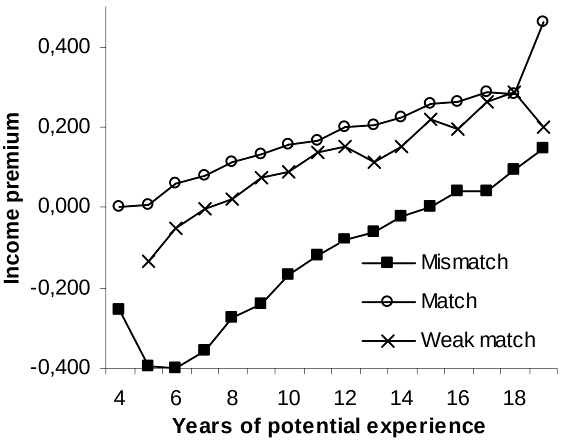

Figure 1. Male income premia for years of experience

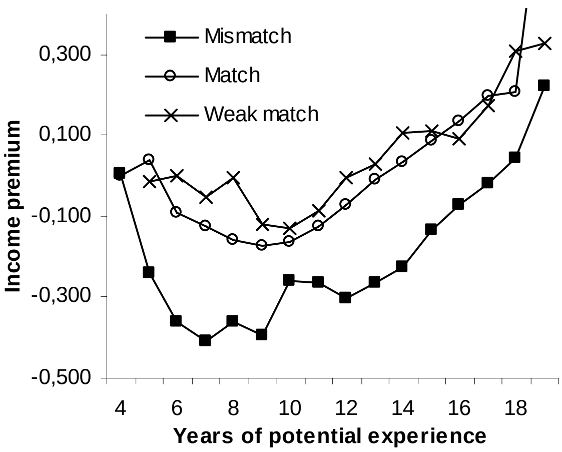

Figure 2. Female income premia for years of experience