Master’s degree graduates in Norway: field of study and labour market outcomes

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Abstract

The main purpose of this article is to analyse to what degree master’s degree education in Norway enhances employability through enhancing or signalling generic competence, or through enhancing specialized competence.

The methodological approach is to first analyse the links between educational group, economic activity and sector, using a relatively detailed categorization with 18 educational groups, 10 economic activities and two sectors, by using multiple correspondence analysis. Educational groups with strong links to certain economic activities are categorized as specialized education, otherwise generic. In the next step we analyse how the distinction between specialized and generic education affects the transfer to employment.

The main data source for the analysis is the NIFU Graduate Survey for the period 1995–2015, where data on graduate numbers as well as detailed information about graduate employment are collected. According to a narrow definition, 39 per cent of the graduates were in specialized education: business administration, information and computer technology, electronic, mechanical and machine subjects and teacher training and pedagogy. Using a broad definition, 65 per cent of the graduates had specialized education, also including languages, humanities and arts other, psychology, health, welfare and sport, law and political science.

The analysis has further shown that generic education graduates had a more difficult transfer to the labour market than those in more specialized education, and that this cannot be explained by generic education being less selective than specialized education.

Keywords: master’s level graduate labour market, competence demand, correspondence analysis

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Master's degree graduates in Norway: Field of study and labour market outcomes

Introduction

Increasing investment in higher education (HE) in advanced economies has also increased concern for investing in the right type of education, which gives the best employment outcomes and economic returns. According to human capital theory (Becker 1964), education increases labour productivity through enhancing skills and knowledge which can be both generic and specialized. Generic competence increases productivity in all types of jobs, while specialized competence increases productivity in some types of jobs more than others. Thus, according to this model, field of study is important for employment outcomes and it is important to have a good match between the dimensioning of the educational system and the demand for specialized competence in the labour market.

In signaling and screening models on the other hand (Spence 1973) the predominant role of education is to signal inherent general abilities, learning aptitude and motivation, and thus put greater emphasis on generic competence. Also, the job competition theory where productivity is viewed as a job attribute and employees compete for the jobs with the highest wages (Thurow 1975, 1979, Hirsch 1977) emphasises the importance of generic competence, as it argues that job-specific skills are predominantly acquired on the job and not in school. Thus, in this model field of study is less important than in the human capital model. The effect of field of study on labour market outcomes is related to differences in degree of selectivity and academic standards.

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The aim of this article is to analyse the causes for differences in labour market outcomes between Norwegian master's degree graduates in different fields of study; is it in accordance with the human capital model caused by differences in the competence acquired from studying, either a mismatch between supply and demand for specialized competence or differences in employability in general manner, or is it more in accordance with signaling and screening models caused by differences in selectivity and person-related generic competence?

Earlier studies

In a study of mechanisms for the effect of field of study on the transition from higher education to work Klein (2010) concludes that lack of occupational specificity is partly responsible for difficulties in labour market entry of graduates from "soft fields" such as humanities and social sciences, whereas selectivity is not important.

Glebbek, Wim & Schakelaar (1989) propose a model called the training cost model where it is assumed that employers hire employees with the lowest expected training cost, which depends on both specialized and generic competence, to analyse the causes for relatively poor employment outcomes for Dutch sociologists, concluding that low selectivity is the main explanation.

Reimer, Noelke & Kucel (2008) find that educational expansion increases differences between fields of study in labour market chances. The explanation is that educational expansion lead to a deterioration of the signal value from less academically challenging and less selective fields like the humanities and social sciences.

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Robst (2007) found that 55 per cent of college graduates had jobs that were closely related to the field of study, and that they earned more than graduates with jobs that were only somewhat or not related to field of study. This however varied between fields of study. Graduates with majors that emphasise general skills, like liberal arts, had a higher likelihood of mismatch, but mismatch costs were relatively low.

Corominas, Saurina and Villar (2010) found in a study of the match between university education and graduate labour market outcomes that responsibilities and duties and specific qualifications were most related to degrees in the health sciences, engineering/architecture and experimental sciences, and least for social sciences and humanities.

Kelly, O'Connell and Smyth (2010) found from a graduate follow-up survey higher returns for medicine & veterinary science, education, engineering & architecture, science and computers & IT, than for arts & humanities.

Li & Miller (2013) found in a study of Australian university graduates that those who majored in the natural and physical sciences, agriculture and environment, society and culture, and creative arts and other fields had a relatively high probability of being over-educated. They also found that these differences could be related to differences in funding and supply of graduates between the fields of study.

Norwegian context

Norwegian labour market and educational system characteristics may influence labour market outcomes of the different fields of study in several ways. Part of the Quality Reform in 2003 was to make the system of HE work as a quasi-market by making HE Institutions autonomous

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regarding study programme profile and by linking funding to the number of credits and graduates, thereby giving the HE institutions both incentive and opportunity to adjust to educational demands from the labour market and society, and in turn prevent large differences in employability between fields of study.

A centralised wage bargaining system with small wage differences, a crucial part of the so called “Nordic model” may also be important. Suppressed graduate wages may increase labour market demand but reduce graduate output, resulting in labour market shortage. Graduates’ wages which are higher than they would be with more market-determined wages may on the other hand reduce labour market demand but increase graduate output, resulting in excess supply of graduates in the labour market.

Also, rigid wages may make the firms less willing to invest in to on-the-job-training, and thus to a greater degree prefer to higher educated workers with specialized competence, rather than train them themselves, this follows from the human capital theory. This in turn may increase recruitment to higher education, both generic and specialized education.

Also, a beneficial system of student financing can be thought of as part of the Nordic Model. Increased recruitment to HE induced by this may not be evenly distributed between fields of study. According to Reimer et al. (2008) increasing recruitment to higher education implies a lowering of student abilities, causing more to choose supposedly less demanding subjects such as humanities and arts and social science. Thus, it is possible that the low cost of studying has increased the supply of graduates especially in humanities and arts and other presumably less demanding subjects.

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Despite the beneficial system of student financing of higher education, the percentage of young people who are currently expected to complete tertiary education in Norway is lower than OECD average (OECD 2016). Compared with other OECD countries, more graduates complete an education in health and welfare and in education, while fewer complete an education in social sciences, business and law (OECD 2015).

While the number of master grade graduates in Norway more than doubled in the period 1995–2015, the labour market has been largely untouched by this. Unemployment has remained mostly at the same level (see Støren, Næss, Reiling and Wiers-Jenssen 2014, Støren 2018). The percentage overeducated increased in the period 1995–2003, but that was before graduate numbers started to increase rapidly. After that the percentage overeducated has generally remained at the same level. Overeducation is particularly high among graduates in humanities and arts, during the whole period.

Methodological approach

The methodological approach consists in two steps; first using correspondence analysis to categorize the educational groups as generic or specialized, and then in the second step use these categories to estimate the effect of specialized versus generic education on labour market outcomes, when also controlling for selectivity and other control variables. This approach allows us to distinguish between three different ways education can enhance employability; through signaling generic competence, through enhancing generic competence and through enhancing specialized competence.

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It is not clear what is or should be reckoned as generic or specialized education. Humanities and social science are the usual typical examples of generic education. But beyond that the literature is rather vague regarding what generic education is. Nor is it certain that all humanities subjects or social science subjects deserve to be labelled as generic. Degree of specificity can also vary much between different subjects within the broader fields of study.

The first step is therefore to analyse the relationships between educational categories and employment in different economic activities and sectors by using multiple correspondence analysis. This method offers a way to measure the degree of specialization of an educational course and also to distinguish between different type of specificities, making full use of the information about the specificity of both the course and the occupation. A strong relationship is interpreted as an indication that specialized competence and thus educational group is important, while a weak relationship is interpreted as an indication that generic competence is most important.

It is interesting to look at both economic activity and sector (business or public), as competence demand can relate to both these variables. The dimensions identified in this analysis, which we interpret as competence dimensions, can then be used to categorize the educational groups into generic and different types of specialized education. We can also see if the relative importance of the competences associated with the competence dimensions has changed over time, using graduation year as a so-called supplementary variable.

In the second step, we analyse how belonging to these different groups affects labour market outcomes measured by unemployment, total mismatch and wages, when also controlling for selectivity measured by high school grades and parents educational level, and other variables, using multivariate analysis. Using three measures is of course better than using one, as they are

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all important parts of the labour market, and also because they may be affected somewhat differently by employability.

Selectivity-measures

Selectivity will be measured partly by the parent's education, partly by the grade level from high school. Many studies show that parent's education is important for socioeconomic success through life (see for example Mastekaasa 2011). High school grades have earlier been used to measure ability in studies of outcome of master grade education in Støren et al (2014).

Correspondence analysis

Two earlier studies which touch upon the theme in this article and which have used correspondence analysis are Martín-Moreno, C., García-Zorita, C., Lascurain-Sánches, M. L., Sanz-Casado, E. (2005) and Nakayama (2014). Martín-Moreno et al. (2005) studied the role that the degree of curricular specialization in academic disciplines played in connection with labour market demand for graduates. By comparing graduates from the Carlos III University of Madrid in three different disciplines in conventional social science, they found by using correspondence analysis that the more specialized discipline received job offers from a broader variety of industries than the disciplines with broader more interdisciplinary curricula. Nakayama (2014) did a multiple correspondence analysis on the relationship between graduates of 13 departments, 21 types of industry, degree and year for the period 1985–2010, for graduates from a Japanese Science and Technology University, and seems to find a development towards increased demand for specialized education.

Data

Data were collected from NIFU's biannual Graduate Survey for the period 1995–2015, which addresses graduates in the spring term six months after graduation. The survey covers nearly all master's level education except for medicine (for an English presentation of the study see NIFU STEP, 2004). The response rate has fallen from 78 per cent in 1995, to 50 per cent in 2015.

In the analysis, we use 18 different educational categories, 10 different economic activities and 2 sectors, as shown in appendix 1. In one analysis we also use follow-up studies aimed at more selected groups of graduates which show the employment situation three years after graduation.

Unemployment

To be defined as unemployed, the graduate is: (a) not in paid work in the reference week, (b) has actively searched for work during the four weeks prior to the reference week, and (c) could take up a job in the reference week. This definition corresponds to that of the International Labour Organisation (ILO).

Total mismatch

Graduates who are unemployed, has involuntary part-time work or are overeducated. Overeducated includes graduates who consider higher education completely unimportant in their job and their education irrelevant to the content of their job.

Monthly salary

Monthly salary is gross monthly salary not including overtime, bonuses or other extra income, for fulltime workers.

Main results from correspondence analysis

There are several different methods for choosing the appropriate number of dimensions identified in the correspondence analysis. One is the scree plot test where we use a scree plot, shown in figure 1. The figure shows modified rates of variance estimated in the correspondence analysis, measured along the vertical axis. We have used modified rates because they often give a better expression of how important the dimensions are, than the actual variance (Le Roux & Rouanet (2010):39), which often are very low in multiple correspondence analysis. In the correspondence analysis, the estimated dimensions will have declining percentage variance explained. According to this test, one should choose the dimensions that are on the steep part of the curve. When the curve flattens out, one can assume that differences in rates are due to random variation. In this case, only one dimension is certain. However, we have also included dimensions two and three, since the following analysis shows that they also have meaningful interpretations.

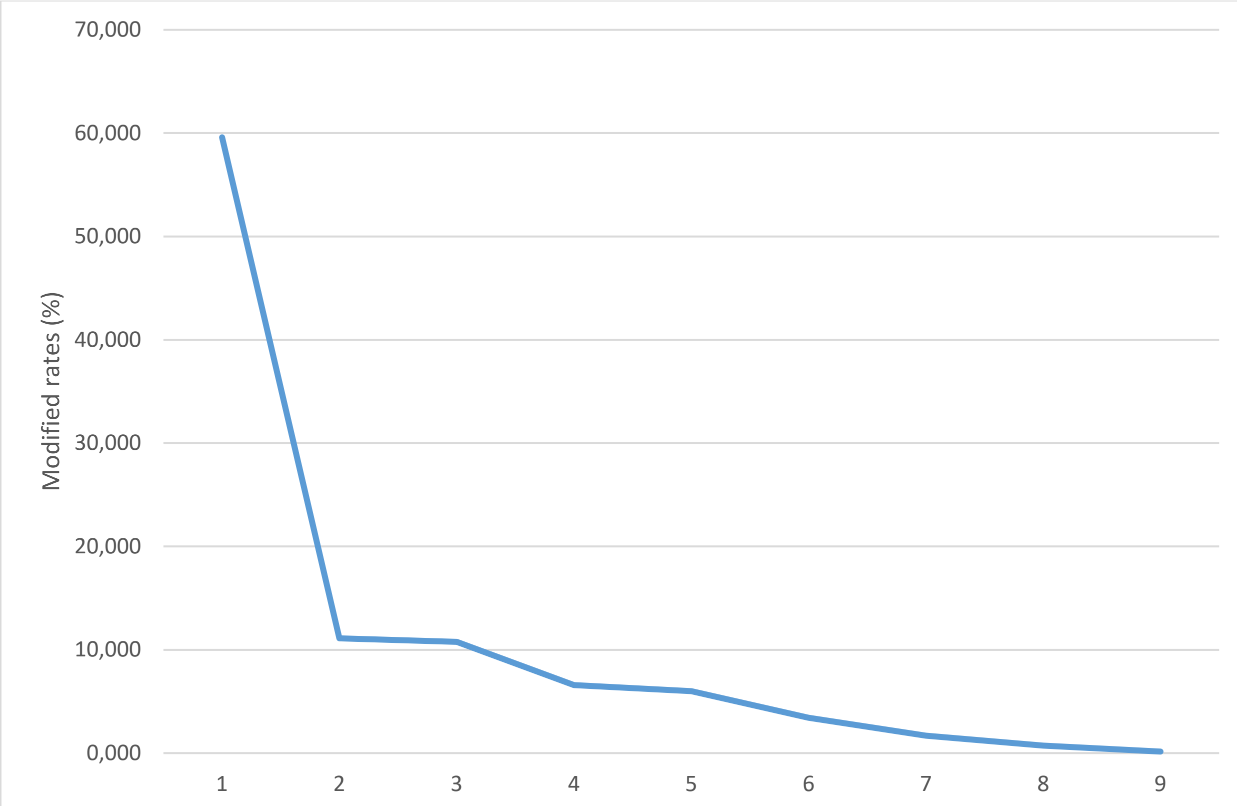

Figure 1. Scree plot – modified rates of variance.

Figures 2 and 3 show the categories which had high scores on these dimensions, and thus tell us what their interpretation should be.[1] Dimension 1 clearly represents an opposition between the business sector and the public sector. We find high negative scores for education typically aimed at the business sector: business administration, information and computer technology and electronic, mechanical and machine subjects. Conversely, we find a large positive score for teacher training and pedagogy and health, welfare and sport.

[1] As is common the selected categories are categories with a contribution above average, which then can be assumed to be due to a real contribution and not only random variation. Average contribution = 1/number of categories = 1/30 = 3.3%. However, to include categories that seem meaningful we have used the threshold value 2.1% for educational categories.

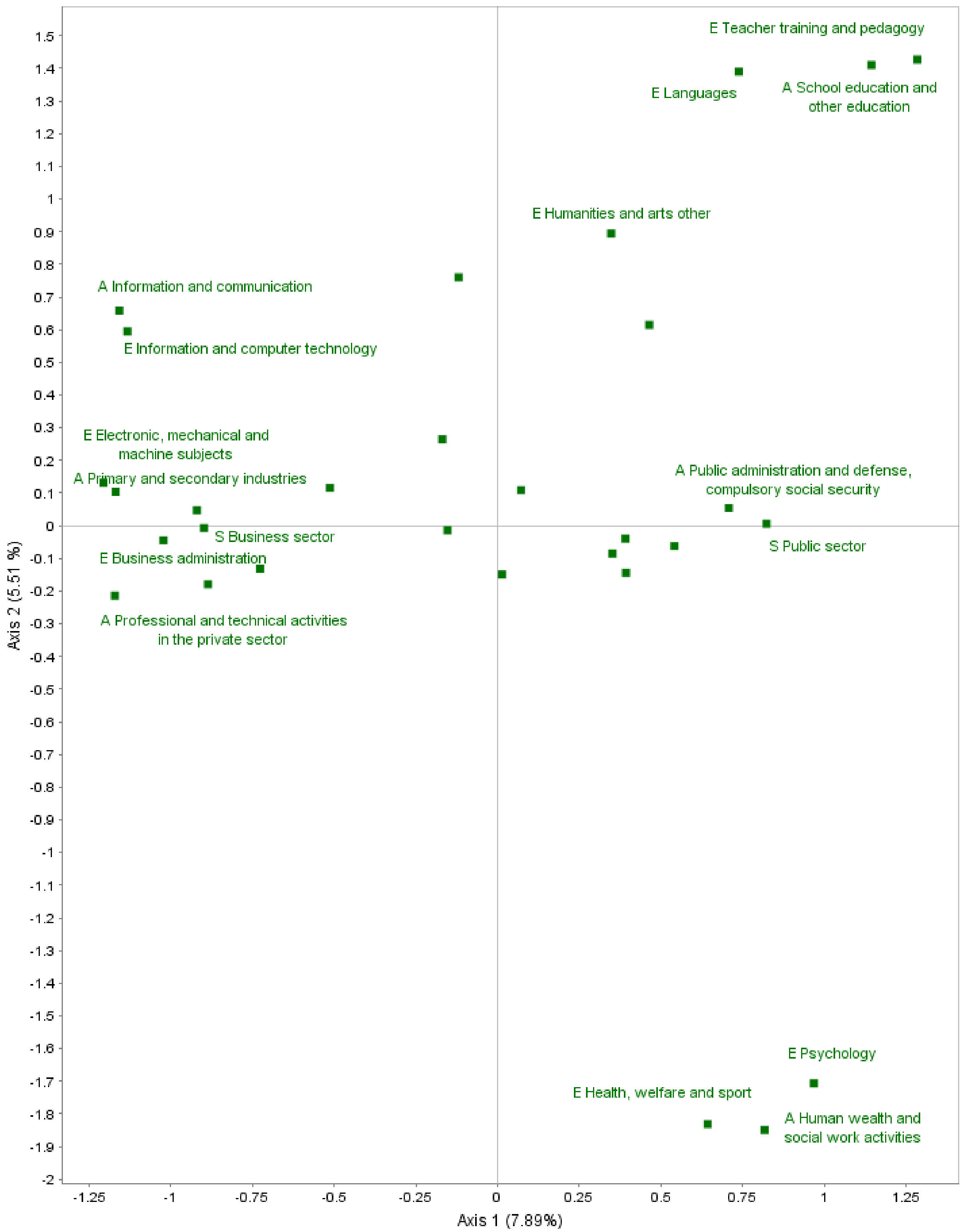

Figure 2. Category scores dimensions 1 and 2.

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Regarding economic activities, we find correspondingly high negative scores for many categories related to the business sector: primary and secondary industries, professional and technical services in the private sector, information and communication; while we find high positive scores for public administration and defence, compulsory social security, school education and other education and human health and social work activities belonging to the public sector. We also find a high negative score for the sector-category business sector, and a high positive score for the public sector.

Dimension 2 clearly reflects an opposition between school education and teaching on one hand, and healthcare on the other. We find high positive scores for the educational groups teacher training and pedagogy, languages and humanities and arts other, and for the economic activities school education and other education, while we find high negative scores for the educational groups psychology and health, welfare and sport, and for the economic activity human health and social work activities.

We also used graduation years as supplementary variables. We have not shown any score for this variable in the figure, because there were none over the chosen threshold value of 0.5. This implies that there has not been any significant change in the relative importance of the competences associated with the two dimensions during the observation period, in the graduate labour market.

Figure 3 show that dimension three is related to law and public administration. We find high positive scores for the educational groups law and political science, and for the economic activity public administration; compulsory social security. Neither did we find that graduation year had any significant effect for this dimension.

Based on these results we use two definitions of generic or specialized competence, a narrow definition where only those educational groups which had a large contribution on dimension 1 is included, and a broad definition where also those educational groups which had large contributions on dimension 2 and 3 are included.

Narrow definition of specialized education:

- Business sector education: business administration, information and computer technology, electronic, mechanical and machine subjects

- Public sector education: teacher training and pedagogy, health, welfare and sport

- Generic education: languages, history and philosophy, humanities and arts other, political science, sociology, psychology, law, social science other, biology, physics and chemistry, building and construction, natural sciences, vocational and technical subjects, other and primary industries

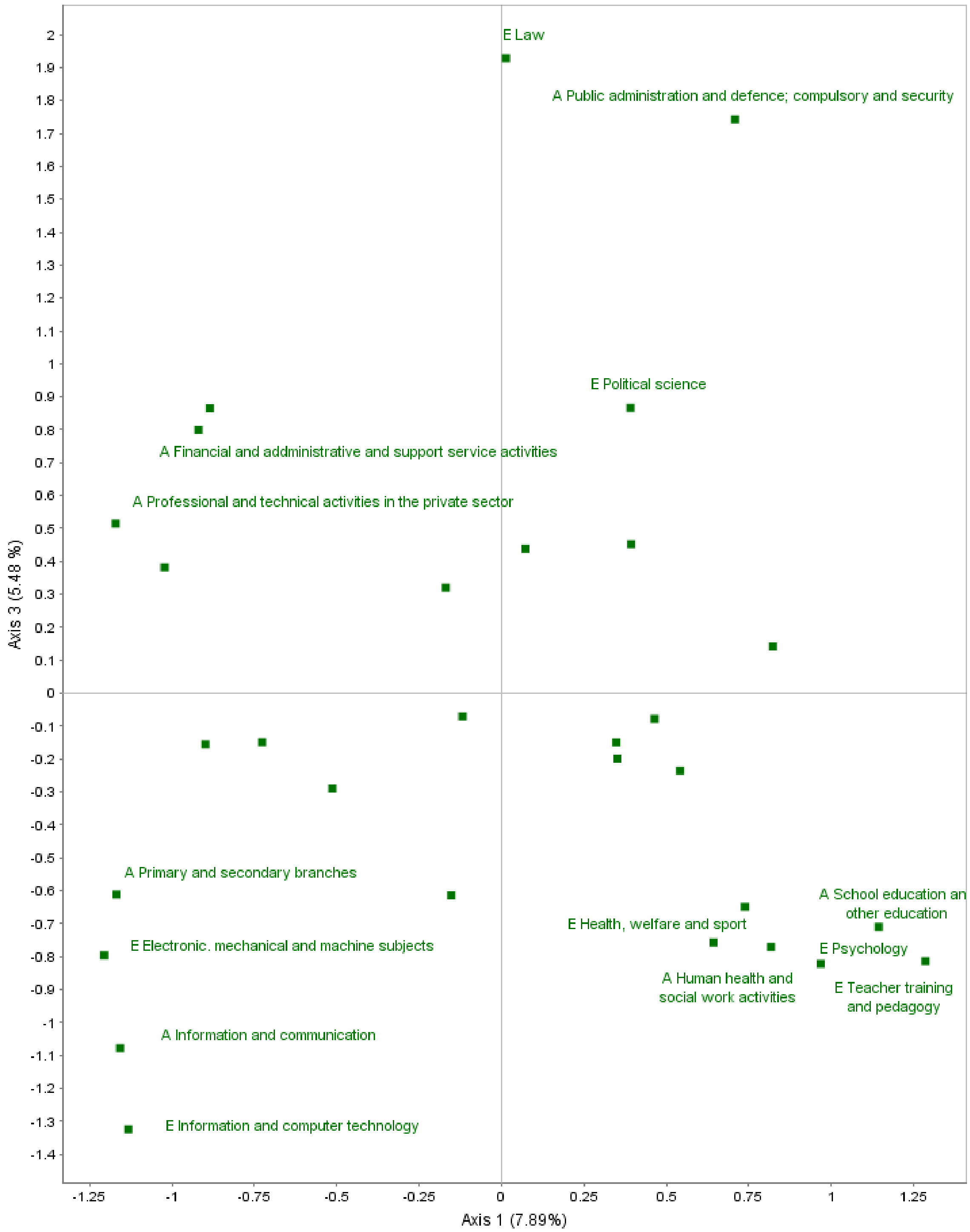

Figure 3. Category scores dimensions 1 and 3.

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Using the broad definition, public sector is split into teacher training and healthcare education, while we also add law:

- Business sector education: business administration, information and computer technology, electronic, mechanical and machine subjects
- Teacher training: teacher training and pedagogy, languages, humanities and arts other
- Healthcare education: psychology, health, welfare and sport
- Law: law, political science
- Generic education: history and philosophy, sociology, social science other, biology, physics and chemistry, building and construction, natural sciences, vocational and technical subjects other, and primary industries

The only subject belonging to humanities and arts that was generic according to this definition was history and philosophy. Not all social science subjects were categorized as generic either; political science was associated with law and public administration, which also seems intuitive. In addition, we found that natural science subjects such as biology and physics and chemistry, and closely related subjects such as vocational and technical subjects, other, and primary industries were generic. This may seem quite reasonable. Graduates with this type of education work in quite different types of employment, teaching, research and industry. In addition, building and construction was categorized as generic, which might seem less intuitive and indicate that the approach used in this article also may have its weaknesses.

According to the narrow definition, 39 per cent of the graduates had specialized education. According to the broad definition, the percentage was 65.

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Changes in graduate output

According to Reimer et al (2008), the expansion of higher education in modern societies has led to an increasing number of less able students who choose supposedly less academically challenging studies they can succeed in. This implies that an increasing proportion of the graduates should have generic education.

However, this in turn may create an oversupply of graduates for this type of education, leading to a worsening of labour market outcomes, thereby dampening the effect of this mechanism. Figure 4 shows the development of the distribution of graduates on categories in the narrow categorization. The figure shows that in Norway there has been a substantially steady declining percentage of graduates with generic education, while there has been an increasing percentage having education in public sector disciplines. This development may however reflect that teacher training education and also some healthcare educations have been upgraded from bachelor education to master's degree education.

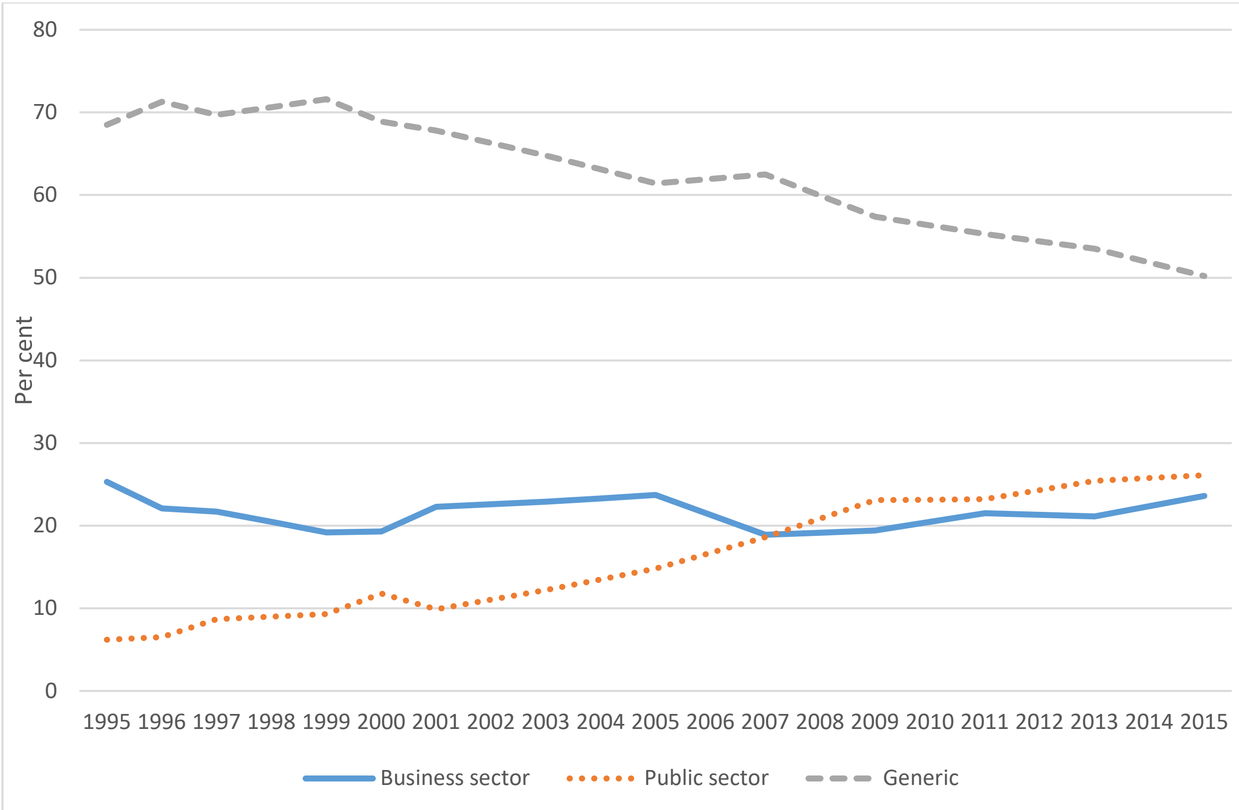

Figure 4. Percentage of graduates with specialized education or generic education – narrow definition.

Figure 5 shows the distribution of graduates in categories using the broad categorization. Also, here we see a steady decline in the percentage of graduates with generic education, and also for law. A master's degree has become increasingly common for both the categories of public sector education, health, welfare and sport and teacher training.

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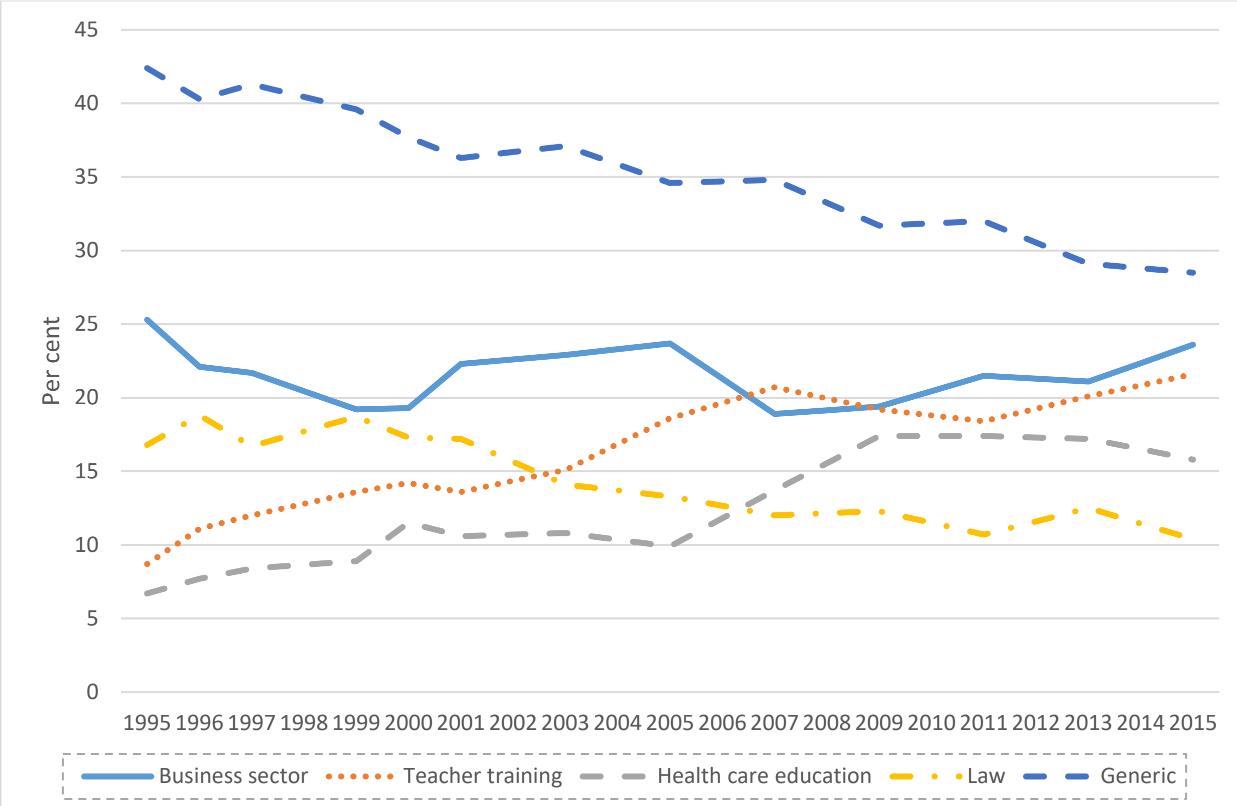

Figure 5. Percentage of graduates with specialized education or generic education – broad definition.

Labour market outcomes

In this section, we will look at how belonging to the specialist groups we have arrived at in the previous section affects labour market outcomes, measured by unemployment and other types of employment mismatch and wages, both six months and three years after graduation.

In table 1 where we have shown the unemployment rate six months after graduation using the narrow categorization, we see that the unemployment rate is lower for the two specialized groups during the whole period, than for generic education. However, the difference between business sector education and generic education is relatively small. The unemployment rate has remained at the same level for all three categories.

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Table 1. Unemployment rate (per cent) in labour force, by narrow categories and educational groups. 1995–2015.

	1995-2000	2001-2007	2009-2015	Total
Business sector education	6,2	7,7	7,5	7,1
Business Administration	*5,7*	*6,3*	*6,4*	*6,1*
Information and computer technology	*4,9*	*7,8*	*10,1*	*7,6*
Electronic, mechanical and machine subjects	*8,0*	*11,1*	*9,5*	*9,4*
Public sector education	2,6	2,2	3,2	2,8
Teacher training and pedagogy	4,6	3,1	2,5	3,0
Health, welfare and sport	1,6	1,4	3,7	2,6
Generic Education	*8,8*	*7,7*	*8,5*	*8,4*
Languages	4,5	3,7	6,6	4,6
History and philosophy	*8,8*	*9,0*	*11,1*	*9,6*
Humanities and arts other	6,0	6,3	6,2	6,2
Political science	7,4	5,8	7,4	6,9
Sociology	*3,4*	*10,3*	*6,1*	*8,6*
Psychology	3,4	3,8	5,3	4,3
Law	11,7	6,9	7,2	9,3
Social science other	*11,2*	*8,2*	*10,9*	*10,1*
Biology	*9,7*	*11,9*	*12,9*	*11,3*
Physics and chemistry	*10,6*	*10,2*	*10,3*	*10,4*
Building and Construction	*8,9*	*9,3*	*7,4*	*8,4*
Natural sciences, vocational and tech. subjects, other	*8,7*	*8,2*	*8,8*	*8,6*
Primary industries	*5,5*	*6,9*	*7,8*	*6,2*
Total	*7,7*	*6,9*	*7,0*	*7,2*

Table 2 show the unemployment rate for specialized and generic education according to the broad definition of specialized education. The two new categories of specialized education introduced with this categorization, teacher training and healthcare education, do have relatively low unemployment rates. The specialized category law, on the other hand, has relatively high unemployment. On average for the whole period, the unemployment rate was lower for all the four specialized groups than for the generic group.

For all five categories, the unemployment level has remained at roughly the same level during the observation period.

Table 2. Unemployment rate (per cent) in labour force, by broad categories. 1995–2015.

	1995-2000	2001-2007	2009-2015	Total
Business sector education	6,2	7,7	7,5	7,1
Teacher training	*5,0*	*4,5*	*4,1*	*4,4*
Healthcare education	*2,2*	*2,1*	*4,1*	*3,1*
Law	*10,8*	*6,6*	*7,3*	*8,5*
Generic Education	*9,1*	*9,3*	*10,0*	*9,4*

When in table we 3 look at the total percentage of employment mismatch, including involuntary part-time employment and overeducation, using the narrow categorization, we find an even clearer distinction between specialized education and generic education; the percentage which was mismatched was much higher for generic education than for specialized education.

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Table 3. Total percentage mismatched, by narrow categories and educational groups. 1995–2015.

	1995-2000	2001-2007	2009-2015	Total
Business sector education	*10,1*	*15,6*	*12,8*	*12,8*
Business Administration	*10,3*	*14,9*	*11,7*	*12,1*
Information and computer technology	*11,2*	*18,6*	*14,7*	*14,4*
Electronic, mechanical and machine subjects	*11,2*	*18,6*	*14,7*	*14,4*
Public sector education	*7,4*	*11,0*	*14,4*	*12,2*
Teacher training and pedagogy	7,7	11,2	12,1	11,2
Health-, welfare and sport	7,2	10,9	16,3	13,0
Generic education	20,3	24,0	24,2	22,7
Languages	22,8	30,9	30,6	27,0
History and philosophy	*29,8*	*37,9*	*39,5*	*36,1*
Humanities and arts other	23,2	28,6	28,3	27,2
Political science	20,2	22,8	22,9	22,1
Sociology	*24,1*	*27,1*	*31,8*	*26,8*
Psychology	7,4	7,8	15,0	10,5
Law	21,8	14,5	17,7	18,7
Social science other	*24,5*	*29,6*	*31,4*	*28,9*
Biology	*27,4*	*30,4*	*30,9*	*29,3*
Physics and chemistry	*17,2*	*21,4*	*20,9*	*19,3*
Building and construction	*12,0*	*15,7*	*12,9*	*13,3*
Natural sciences, vocational and tech. subjects, other	*15,5*	*18,0*	*16,2*	*16,4*
Primary industries	*14,6*	*25,0*	*21,9*	*18,7*
Total	*16,9*	*20,3*	*19,2*	*18,8*

The broad categorization seems perhaps less useful in explaining differences in mismatch shown in table 4; the percentage mismatched is relatively high for the two specialized categories teacher training and law. It is however low for healthcare education, so the percentage mismatched for the generic group is slightly higher than with the narrow categorization. On average for the whole period, mismatch was lower for all the four specialized groups, than for the generic group.

Mismatch has increased for all the categories except law, and especially for healthcare education there has been a large increase.

Table 4. Total percentage mismatched, by broad categories. 1995–2015.

	1995-2000	2001-2007	2009-2015	Total
Business sector education	*10,1*	*15,6*	*12,8*	*12,8*
Teacher training	*18,6*	*22,1*	*19,1*	*20,0*
Healthcare education	7,3	10,0	16,1	12,4
Law	*21,4*	*17,2*	*19,9*	*19,7*
Generic Education	*20,3*	*26,8*	*25,7*	*24,0*

Using the narrow categorization, figure 6 show that average wages for full-time employed have been higher for specialized education than for generic education during the whole period (here we do not have data for 2015). In relative terms, the difference between public sector education and generic education has been slightly reduced during the observation period. The difference between business sector education and generic education has on the other hand been slightly increased.

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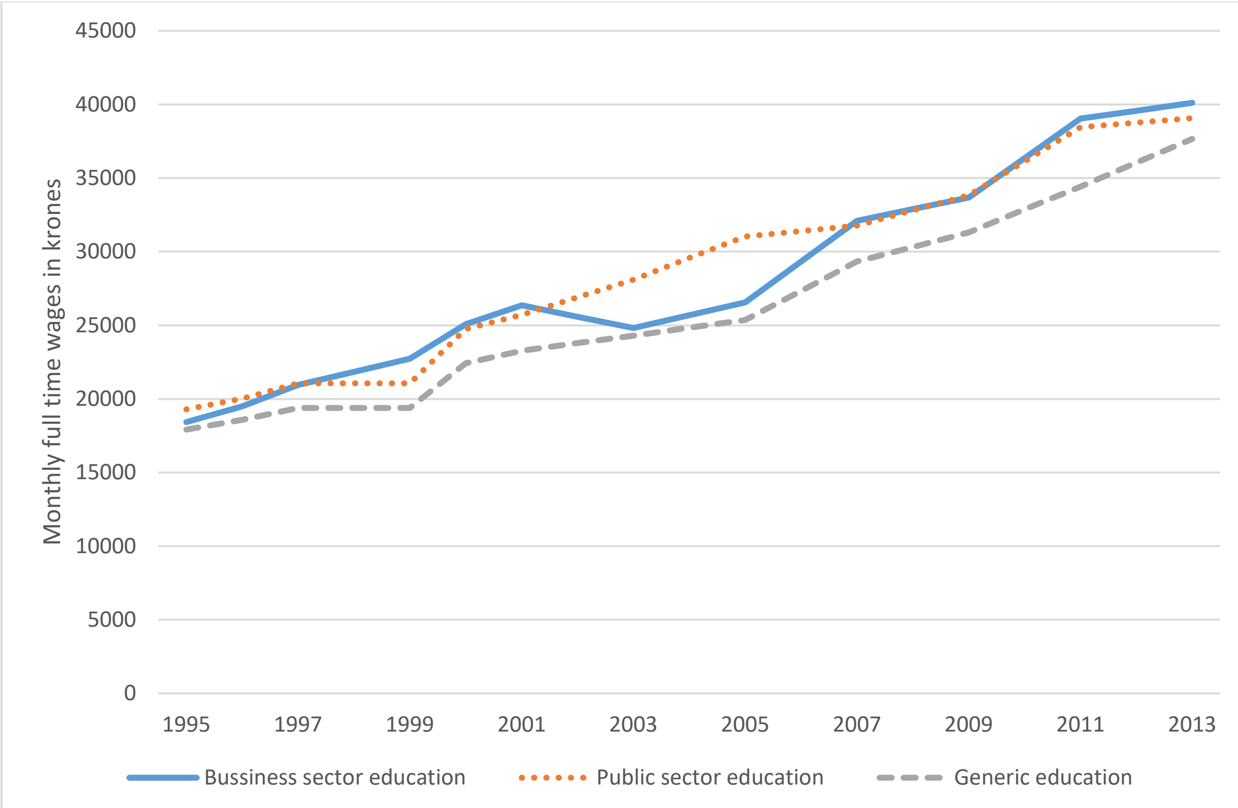

Figure 6. Monthly pre-tax normal fulltime wages, for narrow categories. 1995–2013.

Figure 7 shows the average wages for the different categories using the broad definition. The figure shows that wages have been at a higher level for business sector education and for healthcare education, than for the other groups. There is not much difference between the three other groups. While wages were highest for healthcare education at the beginning of the period, wages have increased the most for the business sector group and have been highest for this group in the latest surveys.

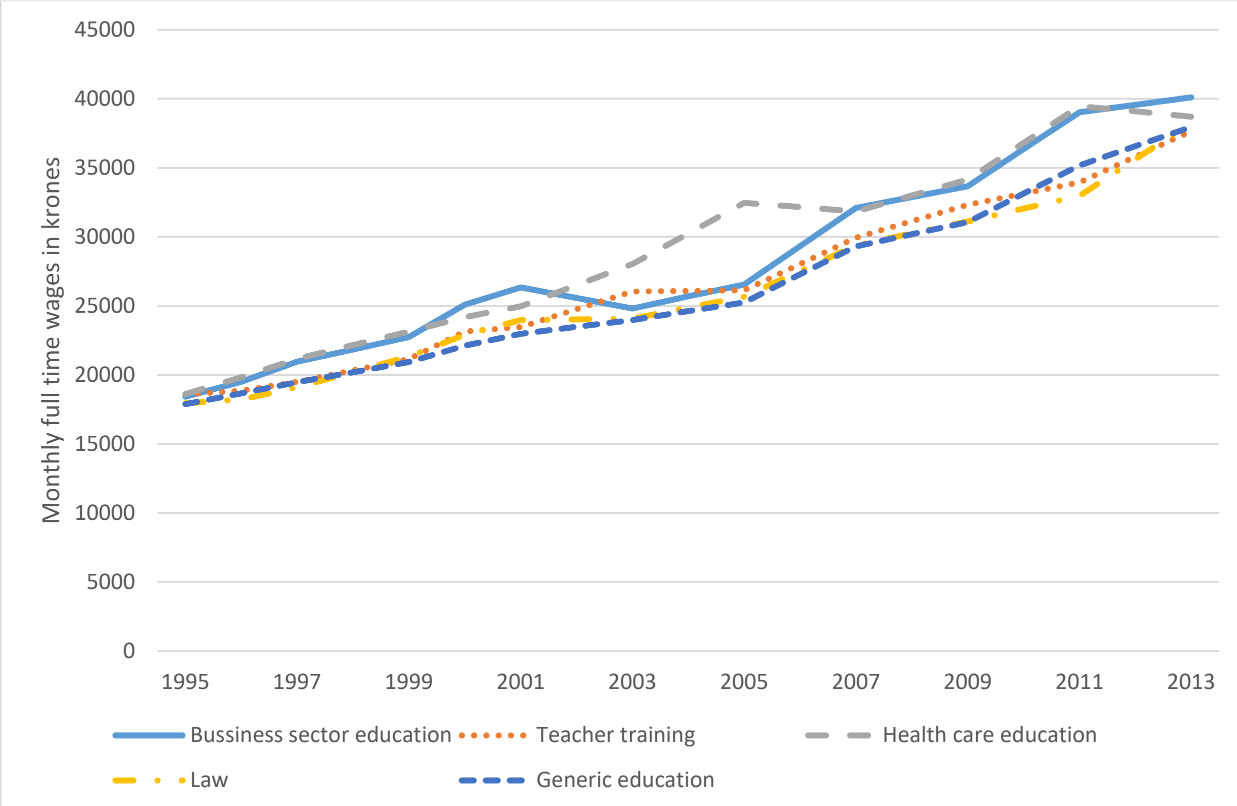

Figure 7. Monthly pre-tax normal fulltime wages, for broad categories. 1995–2013.

Low selectivity for generic education?

In table 5, we looked at grades from high school, for generic and specialized education. For this we only have data from 2003. The table shows that there is not much difference between specialized and generic education. In fact, high school grades were the lowest for public sector education, which had the lowest unemployment rate. Using the broad definition, we see that it was teacher training education which had the lowest high school grades. The results are in accordance with Klein's conclusion (2010), that poorer employment for generic education than for specialized education cannot be attributed to low selectivity.

Table 5 Average high school grades for specialized and generic education. 2003–2015.

	Lower than 3	3 – 3,9	4, –4,9	5,0 or higher
Narrow definition:				
Business sector education	*1,5*	*10,3*	*52,2*	*36,1*
Public sector education	0,4	12,3	57,8	29,2
Generic education	0,7	9,3	55,7	34,3
Broad definition				
Business sector education	1,5	10,3	52,2	36,1
Teacher training	1,0	13,9	60,6	24,5
Healthcare education	0,4	7,4	53,8	38,4
Law	*0,5*	*7,5*	*53,2*	*38,8*
Generic Education	*0,8*	*10,1*	*56,1*	*33,0*
Total	*0,9*	*10,1*	*55,7*	*33,6*

In table 6 we look at the percentage of graduates with parents with higher education. Using the narrow definition, we find that graduates with public sector has a lower percentage of parents with higher education than the other two groups, and especially regarding parents with four years or more with higher education. Graduates with generic education had the highest percentage of parents with higher education.

Using the broad definition, we find that graduates with teacher training had the lowest percentage of parents with higher education. Also, for healthcare education the percentage was relatively low. Graduates with generic education had the highest percentage of parents with higher education also when we use the broad definition.

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Table 6 Percentage of graduates with parents with higher education, for specialized and generic education. 2003–2015.

	Parent had 1-3 years with higher education	Parent had 4 years or more with higher education	Total
Narrow definition:			
Business sector education	*27,0*	*44,5*	*71,5*
Public sector education	23,2	37,1	60,3
Generic education	24,8	47,9	72,7
Broad definition			
Business sector education	27,0	44,5	71,5
Teacher training	22,3	41,5	63,7
Healthcare education	23,5	43,3	66,8
Law	*23,3*	*48,4*	*71,7*
Generic Education	26,4	46,7	73,1
Total	*24,9*	*44,9*	*69,8*

Multivariate analysis

In this section, we want to see if specialized education reduces the risk for unemployment or mismatch compared to generic education, or increase wages, using multivariate analysis. We use both the narrow definition and the broad definition. We also want to see if this to some degree can be explained by selectivity. We have therefore estimated two models, one model where we do not include selectivity measures, to estimate the total effect of specialized education, model 1, and one model where we also control for the selectivity measures, model 2. We do not include other individual variables that may also be related to selectivity.

Selectivity measures

Parents educational level is the level for the parent with highest educational level and have the values: 0 = not higher education, 1 = bachelor degree, 2 = master's degree or equivalent.

For high school grades the categorization in table 6 is used, with the value 0 for lower than three and the value 6 for 5,5 or higher.

Results

The results are shown in table 7, 8 and 9. In model 1 using the narrow definitions, we find that that public sector education significantly reduces the risk of unemployment, and that both categories of specialized education significantly reduces the risk of mismatch and increase wages. Using the broad definition we find that all the categories of specialized education significantly reduces the risk of unemployment and mismatch, and also significantly increase wages, with the exception of law.

In model 2 we find that high school grades significantly reduce the risk of unemployment and mismatch and increase wages. Parents educational level does not have a significant impact on unemployment and mismatch but have a significant negative effect on wages. This may indicate that parent's educational level not is very useful as a selectivity measure, but it may also be because graduates with parents with a high educational level put greater emphasis on their scientific interest than wages, compared to other graduates.

The magnitude of the estimated coefficients is largely the same as in model 1. This imply that the estimated effects of the educational categories not can be explained by differences in selectivity.

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In particular also these results imply that the relatively poor labour market outcomes for generic education cannot be explained by low selectivity.

Table 7 Multivariate analysis unemployment. 2003–2015.

	Model 1		Model 2	
	Coefficient	St.a.	Coefficient	St.a.
Narrow categorization				
Business sector education	-0.057	0.065	-0,050	0.067
Public sector education	-1.122**	0.096	*-1.097***	*0.098*
High school grades			*-0.241***	*0.043*
Parents educational level			*0,032*	*0,034*
Constant	-2.416**	0.034	-1.712**	0.139
- 2 Log likelihood	10 278.504		9 760.653	
Broad categorization				
Business sector education	-0.237**	0.069	-0.226*	0.071
Teacher Training	-0.890**	0.089	-0.930**	0.093
Healthcare education	-1.140**	0.107	-1.048**	0.109
Law	-0.329**	0.088	-0.305**	0.090
High school grades			-0.231**	0.043
Parents educational level			0.044	0.034
Constant	-2.236**	0.042	-1.581	0.158
- 2 Log likelihood	10 258.581		9 739.526	

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Table 8 Multivariate analysis total mismatch 2003–2015.

	Model 1		Model 2	
	Coefficient	St.a.	Coefficient	St.a.
Narrow categorization				
Business sector education	-0.648**	0.047	-0.655**	*0.048*
Public sector education	-0.729**	0.049	-0.716**	*0.050*
High school grades			-0.232**	*0.027*
Parents educational level			-0.014	*0.021*
Constant	-1.124**	0.021	-0.376**	*0.090*
- 2 Log likelihood	20 378.376		19 552.062	
Broad categorization				
Business sector education	-0.751**	0.051	-0.750**	0.052
Teacher Training	-0.344**	0.048	-0.358**	0.050
Healthcare education	-0.762**	0.058	-0.708**	0.059
Law	-0.418**	0.058	-0.392**	0.059
High school grades			-0.204**	0.028
Parents educational level			0.003	0.021
Constant	-1.021**	0.028	-0.289**	0.092
- 2 Log likelihood	20 419.292		19 573.857	

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Table 9 Multivariate analysis ln(wages) for full time employed 2003–2013

	Model 1		Model 2	
	Coefficient	St.a.	Coefficient	St.a.
Narrow categorization				
Business sector education	0.085**	0.006	0.082**	*0.006*
Public sector education	0.121**	0.006	0.122**	*0.007*
High school grades			0.041**	*0.004*
Parents educational level			-0.008**	*0.003*
Constant	10.921**	0.003	10.170**	*0.013*
R^2	0.036		0.045	
Broad categorization				
Business sector education	0.083**	0.007	0.079**	0.007
Teacher Training	0.032**	0.008	0.033**	0.008
Healthcare education	0.119**	0.008	0.110**	0.008
Law	-0.001	0.008	-0.005	0.008
High school grades			0.036**	0.004
Parents educational level			0.003**	0.003
Constant	10.924**	0.004	-0.011**	0.013
R^2	0.028		0.035	

Conclusions and discussion

The aim of this article has been to analyse the causes for differences in labour market outcomes between Norwegian master's degree graduates in different fields of study; is it caused by a mismatch between supply and demand for specialized competence, or is it caused by differences in selectivity and generic competence?

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By using correspondence analysis, we first identified competence dimensions used to categorize the educational groups as specialized or generic. Using a narrow definition of specialized education, we found two categories of specialized education: business sector education including business administration, information and computer technology and electronic, mechanical and machine subjects, and public-sector education including teacher training and pedagogy and health, welfare and sport. 39 per cent of the graduates belonged to these two categories.

Using a broad definition of specialized education, public-sector education was split into two categories: teacher training which in addition to teacher training and pedagogy also included languages and humanities and arts other, and healthcare education which in addition to health, welfare and sport also included psychology. In addition, we found that law including law and political science should be defined as specialized education. 65 per cent of the graduates belonged to these four categories of specialized education. According to this definition, not all subjects belonging to humanities and arts and social science are generic, whereas natural science is generic.

In contradiction to Reimer et al. (2008), we did not find an increasing percentage of the graduates having generic education; on the contrary, we found a steady decline, using both the narrow and the broad categorization. This however also may be explained by a development of upgrading of teacher training and also healthcare education from bachelor's degree education towards master's degree education.

Throughout the whole period graduates from the specialized categories had better employment outcomes than graduates from the generic group, six months after graduation. On average for the whole period, the unemployment rate six months after graduation was lower for all four specialized groups we found using the broad definition, and total mismatch was also lower than

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for the generic group. Wages for the generic group were also lower than for business sector education and healthcare education.

According to the results, the difference in labour market outcomes was not because generic education is less selective than specialized education. Regarding high school grades, there was little difference in selectivity by specialized education and generic education. And the educational level among the parents was higher for graduates with generic education than for graduates with specialized education. Also, when we estimated the effects of specialized education on unemployment, mismatch and wages using multivariate analysis, the estimated effects were not substantially reduced when we controlled for selectivity, even if high school grades also had a significant effect.

Thus, better employment outcomes for specialized education than for generic education seem to be explained by a demand for specialized competence in the labour market, and not differences in selectivity and generic competence.

Of the specialized groups, healthcare education was the one with best employment outcomes six months after graduation; unemployment or other types of mismatch was low, and wages were high, even though mismatch had increased throughout the period.

Business sector education also had low total mismatch even though unemployment not was particularly low; this seems to be a group relatively unwilling to accept other forms of mismatch such as part-time employment or overeducation. Wages were also high. Teacher training education had low unemployment six months after graduation, but relatively high total mismatch, and relatively low wages. Law had relatively high unemployment and total mismatch six months after graduation, but low wages.

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Appendix Sample

Table A1. Number and per cent of graduates used in correspondence analysis, by educational group. 1995–2015.

	Number	Per cent
Languages	928	3.3
History and philosophy	1,264	4.5
Humanities and arts other	1,718	6.1
Teacher training and pedagogy	2,059	7.3
Political science	1,183	4.2
Sociology	575	2.1
Psychology	978	3.5
Law	2,601	9.3
Social science other	1,645	5.9
Business administration	3,577	12.8
Biology	1,379	4.9
Physics and chemistry	1,256	4.5
Information and computer technology	976	3.5
Electronic, mechanical and machine subjects	1,381	4.9
Building and construction	1,068	3.8
Natural sciences, vocational and technical subjects, other	1,808	6.5
Health, welfare and sport	2,855	10.2
Primary industries	765	2.7
Total	28,016	100.0

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Table A2. Number and per cent of graduates used in correspondence analysis, by economic activity. 1995–2015.

	Number	Per cent
Primary and secondary branches	2,676	9.6
Information and communication	1,656	5.9
Trade and transportation	1,618	5.8
Professional and technical activities in the private sector	3,768	13.4
Financial and administrative and support service activities	1,570	5.6
Public administration and defence; compulsory social security	3,945	14.1
Higher education and research and development	4,443	15.9
School education and other education	3,654	13.0
Human health and social work activities	3,481	12.4
Arts, entertainment and recreation	1,205	4.3
Total	28,016	100.0

Table A3. Number and per cent of graduates used in correspondence analysis, by sector. 1995–2015.

	Number	Per cent
Public sector	14,622	52.2
Private sector	13,394	47.8
Total	28,016	100.0

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