Innovation and Education: Is there a 'Nerd Effect'?

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Abstract

Policy makers are interested in fostering economic growth and employment. Therefore, it is important to know how to boost innovation in an effective way. This paper investigates whether entrepreneurs with technical education are more innovative in high-tech industries than economists. The main contribution to the literature is in using the type of education as main explanatory variable for innovation. To analyze this question, the KfW/ZEW Start-Up Panel between 2007 and 2008 is used. Two independent OLS regressions are conducted for entrepreneurs with university degree and practical education. This strategy considers the potential heterogeneity between different amounts of education. The results suggest that education matters for individuals with a university degree in high-tech industries but not for people with practical education. Having an economics degree is correlated with higher innovativeness. Therefore, for the underlying sample we do not find a 'nerd effect'.

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1 Introduction

Policy makers are interested in fostering economic growth and employment. According to Hasan and Tucci (2010), countries rely on innovative products for economic growth. Therefore, it is important to know how to boost innovation in an effective way. One important factor is education (Cooray (2010)). So far, the literature mainly concentrates on the relation between education and the probability of becoming an entrepreneur or between education and performance. In contrast, the innovation process within start-ups is relatively unexplored. Being innovative does not necessarily coincide with being successful in a monetary sense. Gompers et al. (2005) show that the R&D elasticity of output is less than one. This means that there are many patents with zero business value. Companies can register a patent without ever using it (Gilbert and Newbery (1982)). This decision can be strategically motivated because these firms prohibit competition and maintain their market power. All these reasons show that there is no one-to-one correlation between innovativeness and profits. Until now, only few empirical papers have tried to explain innovation with the type of education as main determinant. Toivanen and Väänänen (2011) investigate whether an engineering degree has an influence on the registration of patents. Individuals with an engineering background have a positive effect on invention (measured as number of patents). However, the authors do not distinguish between different types of firms. The traditional entrepreneurship literature emphasizes the role of large cooperations in the innovation process. According to it, small firms do not contribute to technological change. In contrast, recent empirical studies show that start-ups have a comparative advantage in fostering innovation, as Acs and Audretsch (2005) argue. This paper investigates whether innovation can be explained by personal attributes of the entrepreneur, where the main explanatory variable is the type of education. The central research question is whether entrepreneurs with technical education are more innovative in high-tech industries compared to economists. This potential effect is defined as 'nerd effect'throughout this paper. To analyze this question, the KfW/ZEW Start-Up Panel is used. It contains a sample of German start-up companies

between 2007 and 2008. Two independent OLS regressions are conducted for entrepreneurs with university degree and practical education. This strategy considers the potential heterogeneity between different amounts of education. The results suggest that education matters for individuals in high-tech industries with a university degree but not for people with practical education. Having an economics degree is correlated with higher innovativeness. Therefore, for the underlying sample we do not find a 'nerd effect'.
The paper proceeds as follows: Section 2 provides a literature overview of related topics. Section 3 describes the data set, definitions and provides summary statistics. Section 4 presents the regression results. Furthermore, several robustness checks are conducted. Section 5 summarizes the main results and concludes.

2 Literature

The so-called 'nerd effect'is defined in this paper as a potential comparative advantage of individuals with technical education in innovative activities. Murphy et al. (1991) describe in their empirical analysis college students enrolled in engineering as persons who initiate technological progress while those enrolled in law are characterized as rent seekers. In their theoretical growth model including human capital they provide conditions under which it is more profitable to become rent seeker instead of promoting economic growth. The empirical findings confirm the hypothesis that more engineers promote economic growth wheras in contrast more lawyers decrease it. Their educational approximations are rather weak because they lack detailed information about start-ups and their entrepreneurs on micro basis. In addition, Toivanen and Väänänen (2011) investigate whether an engineering degree has an influence on the registration of patents. They conclude that persons with engineering background have a positive effect on invention. This paper concentrates on the distinction between non-high-tech and high-tech start-ups. Persons with technical education could have a comparative advantage in the high-tech industry because they have more knowledge in their field.

Hypothesis 1 *Entrepreneurs with technical education are more innovative in high-tech industries than entrepreneurs with an economics degree.*

First, the literature on innovation is reviewed. de Mel et al. (2009) propose a model of innovation where the probability of being innovative depends on the entrepreneur's ability. They examine whether the traits of the entrepreneur or firm characteristics are able to explain different types of innovation. The authors use the Sri Lanka Longitudinal Survey of Enterprises between January and May 2008. They distinguish between four different types of innovation: product, process, marketing and organizational innovation. Two independent regressions are conducted: one for the traits of the entrepreneur and one for firm characteristics. The authors find that beside firm size owner characteristics also play an important role for explaining innovation. Thus, the greater the years of schooling and IQ, the more likely it is that an innovation occurs. However, the authors do not include the type of education in their analysis.

Sauermann and Cohen (2010) also have a different focus compared to this study. They look at how employees' incentives influence innovation in companies. Thus, they do not analyze start-ups and concentrate on employees with a doctoral degree. The main explanatory variables are extrinsic (monetary) and intrinsic (non-monetary) motivation. The authors reason that motives are important but they differ in their effects: intellectual challenge and independence show a strongly positive one, while job security and responsibility seem to have a negative effect on innovation.

Further literature discussing innovation is provided by Szymanski et al. (2007). They compare different studies dealing with the effect of innovation on performance. These studies mostly differ in the definition of innovation activity. One central conclusion is that innovation measures that include a dimension for meaningfulness are stronger correlated with performance. Furthermore, the analyzed correlations vary wildly across the models.

Praag and Versloot (2007) discuss the value of entrepreneurship and how entrepreneurship contributes to innovation. Accordingly, they review 19 different empirical contributions from the literature. These empirical studies differ in measuring innovation: some concentrate on quantity, others on quality, commercialization or adoption. According to them, entrepreneurs do not invest more in R&D than their competitors and produce fewer innovations. However, they have a comparative advantage in the production of high-quality innovations and in commercialization of innovations.

In the entrepreneurship literature education or skills are mostly related to entry decision or performance. In the following, an overview of this literature is provided and aspects are presented on which authors focus. Mostly, the definition of education or skills differs among the empirical studies. Parker and van Praag (2006) investigate the effect of schooling and capital constraints on performance for Dutch start-ups with a random cross sample in 1994. They extend the theoretical model by Bernhardt (2000), which relates the effect of credit constraints on profits, using education. The higher the number of years of schooling, the lower the capital constraint is. Education, as well as credit constraints, can be endogenous in explaining profits. The authors reason that higher education leads to fewer capital constraints and therefore to better performance. In addition, more schooling also leads directly to more profitability.

Davidsson and Honig (2003) examine whether and how human and social capital are able to explain entry decision and performance. They use data for Swedish nascent entrepreneurs from a random sample. Human capital is distinguished by explicit and tacit knowledge. Explicit knowledge represents formal education, while tacit knowledge is know-how. The authors reason that education plays an important role for the entry decision but not for performance. More social capital is associated with a higher probability of entrance and better performance.

Backes-Gellner and Werner (2007) explore the effect of eduction as a quality signal for banks and employees for German start-ups in 1998 and 1999. The disparity between high-tech and non-high-tech start-ups is emphasized. According to the authors, the evaluation of high-tech firms is harder for banks and employees because there is no experience with similar products. That is why the information asymmetry is more severe for these industries. They reason that entrepreneurs with higher education can receive better credit conditions in high-tech industries, such that they are less capital constrained and are able to attract high-skilled employees. By contrast, the authors do not find these effects in the traditional start-up industries.

van der Sluis et al. (2008) provide a literature review with empirical papers about the relation between education and entry decision/performance. The findings depend on the underlying definition of entrepreneur, education and performance. The authors highlight that education alone is not able to explain the entry decision. This insignificant effect exists because higher education incorporates two contradicting impacts. High education facilitates the foundation of the start-up but it also raises the reservation utility due to better outside options. However, higher education is associated with better performance.

Dutta et al. (2011) analyze whether and how specialized and diversified education influence the entry decision into entrepreneurship and future wealth prospects (in the sense of performance). Specialized knowledge is defined as entrepreneurship courses that are explicitly designed for nascent entrepreneurs. Diversified education is the attendance of courses that are not necessarily related to entrepreneurship. The authors use data on entrepreneurship alumni between 1988 and 2008 from public universities in Northeast USA. As a result, specialized and diversified education have a significant and positive effect on the probability of starting a new venture. In contrast, these effects are not existent for annual income and net worth.

A similar contribution is provided by Lazear (2005), who defines diversified and specialized skills which are strongly related to education. One major drawback is that he deemphasizes innovation. He proposes a simple theoretical model and argues that entrepreneurs are ‚Jacks-of-all-trades' (JAT). This means that entrepreneurs have to feature many different skills compared to a specialist who is able to specialize completely in one skill. This hypothesis is tested and validated with alumni data from Standford Business School. Therefore, attended courses and prior roles in companies are used as approximations for specialized vs. diversified skills. This comparison takes place within one field of study (business administration).

This hypothesis is also tested for other countries. One study is offered by

Wagner (2003). He uses a German random sample between October 1998 and March 1999. The author confirms the JAT hypothesis. Thus, more professional training and changes in profession lead to a higher probability of being self-employed. In further work, Wagner (2006) has more information on the different kinds of professional trainings, concentrates more on nascent entrepreneurs (compared to self-employed vs. employees) and uses a so-called ‚rare events logistic regression' estimation technique. His overall main results coincide with his earlier work.
As mentioned in the introduction, innovation is essential for economic growth and employment. Whether the type of education has an effect on innovation is therefore an important issue.

3 Data and Summary Statistics

The data used in this paper is the KfW/ZEW Start-Up Panel. The start-ups are identified by the database of Creditreform which reports on the most active economic companies. It is a sample that contains yearly data for German start-up companies between 2005 and 2008. Further information is provided by Fryges et al. (2010). An entrepreneur is defined here as someone who belongs to the persons establishing a start-up. First, the definitions are described.

3.1 Definitions of Basic Variables

The literature shows that there are different methods and strategies for measuring ‚innovation'. Acs and Audretsch (2005) emphasize that innovation and technological change is a process that is not easily measurable. They mention attempts to measure innovation more accurately by using independent experts in the technological field who are able to weight the innovations. Typically input and output variables are used in empirical studies. Having these potential problems of measuring innovation in mind, innovation is approximated in different ways. As basic measures for innovation, a binary input variable indicating whether R&D was conducted (*r&d*) and a binary output variable that indicates whether something new has been released on the market since the foundation (*mrel*) are used. For robustness checks, R&D expenditures per worker (*expend*), the scope of the market release (*new*), a dummy variable whether patents are used today or in future (*pat_use*), a dummy variable whether a product (*prod*) or process (*proc*) innovation is achieved are employed. *expend* is one further input variable for R&D that is used by other studies examining innovation. The advantage is that innovation activity is measured more from an objective point of view (instead of a potential bias resulting from more subjective measures) and can be evaluated at a metric scale. *new* takes value one, if there is no new market innovation, for value two the innovation is at regional level, value three at national level and value four at worldwide level. The variable *pat_use* describes an output variable which is a dummy. In contrast to other measures, it includes a time dimension. The variables *prod* and *proc* are output dummy variables. They concentrate on the type of innovation. The main explanatory variable in this analysis is education. It is measured in two dimensions: the amount is scaled as dummy variable *uni*, which takes value one if the entrepreneur has a degree from university and zero when the person completed a practical education. The second dimension is the field that is studied. Dummy variables are generated for business or economics (*econ*), natural science (*nat*), mathematics or informatics (*mathinf*), engineering (*eng*) and other subjects (*other*). These are only available for entrepreneurs with a university degree. Practical education uses a different notation. Having an apprenticeship in commerce is *comm*. The other fields are technical (*tech*), social (*social*), other services (*othserv*) and other professions (*other_job*).

3.2 Definitions of Control Variables

To control the entrepreneur's personal traits, nationality (*german*), sex (*male*), experience, prior employment situation, foundation motivation and ownership structure are included. Experience is measured in intervals: less than seven years, more than seven and less than 13 years, more than 13 and less than 20 years and more than 20 years. The employment situation immediately before the start of the venture is approximated by dummy variables. An entrepreneur was either self-employed (*sit_ e*), employed (*sit_ em*), unemployed (*sit_ unem*) or not working (*sit_ ne*). Motivation is classified as working independently, realising a business idea, improper employment opportunities, escape from unemployment, encouragement by former employer or tax incentives. Ownership structure is measured as the share that is financed by the entrepreneur himself (*fin_ sh*) and as external investors (*fin_ ext_ sh*). The higher the entrepreneur's share, the greater the rent he is able to extract in future and therefore the higher the incentive to be successful in innovation. Beside these personal traits, firm characteristics are also included as further control variables. Firm size is determined by the number of different types of employees: amount of full time, part time, mini, family members, trainees, freelancer, interns and temporary employees. The sum of all these types is illustrated in *employment*. Another component is the quality of this employment pool: the number of employees having no apprenticeship (*sh_ l*), an apprenticeship (*sh_ m*) or a university degree (*sh_ h*) is embedded. Competition structure may affect innovative activity as well. *lcomp* describes low competition when the start-up faces less than six other companies as competitors, *mcomp* identifies between six and twenty companies as competitors and *hcomp* stands for more than twenty companies. ZEW categorizes industries into high-tech and non-high-tech industries. This definition is adopted in the following. The classification is described in Table 1.

3.3 Summary Statistics

This subsection starts with the provision of some stylized facts based on the the sample. We have an unbalanced panel for German start-ups founded in 2007 and 2008 with approximately 7,000 observations. Table 2 provides a description for our used dependent variables (innovation)[1]. Note that for our robustness checks pat_use, prod and proc exhibit some data limitations. The first indicator shows that 23% of the start-ups are temporarily or perma-

[1]Minimum and maximum values are not reported due to provision restrictions. However, these values are very similar compared to the reported intervals.

nently engaged in R&D. Furthermore, 21% have released a market innovation since foundation. These two variables only illustrate a part of the whole innovation process. Other variables are investigated that can illustrate further aspects. Each start-up invests 2,920 euro per employee on average. The high standard deviation indicates that there is a high fraction of start-ups investing no money. *new* describes the average innovation as relatively small in scope. According to *pat_use*, only a small fraction of start-ups (approximately 8%) are engaged today or in future in patenting. 37% of start-up innovations are connected to products, 27% exhibit innovation in processes. Table 3 presents the personal traits and firm characteristics.
First, the distribution of education is described. approximately 38% have a university degree. From these, 46% studied engineering, 27% economics, 12% mathematics or informatics, 12% natural science and 15% another subject. As a result, most start-ups in the sample were founded by persons with technical background. These numbers are compared with individuals who have a practical education: most have either a technical (62%) or commercial (26%) education. Some studied social science (8%), other services (7%) or completed an apprenticeship in other jobs (4%). Figure 1 describes the distribution among both industries for university degree. There is a higher fraction of engineers, natural scientists and mathematics/informations in the high-tech industry. In contrast, entrepreneurs with business/economics degree are more represented in the non high-tech industry. The similar observation holds true for apprenticeship as shown in Figure 2. More entrepreneurs with commercial or other services are active in the non high-tech industry, while those with technical and social science are engaged in the high-tech industry. Next, the other personal traits are examined. 95% of the entrepreneurs are German, 80% are male. Most entrepreneurs (61%) were employed in a firm prior to the start-up, only 22% were self-employed before the start-up was found. Finally, the firm characteristics are shown. 41% of start-ups are engaged in the high-tech industry, 27% founded by teams. The average entrepreneur contributes 20% of the assets by himself and receives 12% from outside financiers. Many start-ups have only few employees (4-5) and, if so, the number of employees with practical education is highest. 56% face high

competition in their environment.

4 Empirical Results

4.1 Baseline Regressions

In the following, we want to test our hypothesis we stated before in our theoretical section: entrepreneurs with technical education are more innovative in high-tech industries than entrepreneurs with an economics degree. Accordingly, we use *r&d* and *mrel* as dependent variables. They describe different parts of the overall innovation process. *r&d* can be interpreted as input variable, *mrel* as output variable. Thereafter, other innovation proxies are used for robustness checks. Table 4 presents the correlation among the dependent variables. It shows that the variables are correlated to some extent. *mrel* and *new* are highly correlated because the first variable is approximated by using the second one. However, the correlation indicates that all other proxies do not capture the same thing. To establish a relationship between innovation and education the following equations are estimated

$$\mathrm{r\&d}_i = \alpha + \beta x_i + \gamma z_i + u_i \tag{1}$$

$$\mathrm{mrel}_i = \alpha + \beta x_i + \gamma z_i + u_i \tag{2}$$

where x_i is the vector of explanatory variables (in this case the variables for education) and z_i the vector of control variables (other personal traits and firm characteristics). We estimate the equations using OLS for the different types of education, one for having a university degree and one for apprenticeship. Although the dependent variable is a dummy variable, we do not estimate a probit model as baseline regression for one special reason: the probit model structure imposes normality as restrictive assumption for the cumulative distribution function. When a saturated model is involved, Angrist and Pischke (2008) suggest that using OLS is better for identifying causality. This is only true when there is a random sample treatment in the data[2]. Ideally, we would be able to reveal the relation between education and innovation experimentally meaning that the entrepreneurs should be randomly endowed with different types of education. Since the implementation of such an experiment is obviously impossible, we have to approximate such a situation as best as possible. Our identification strategy is to control for most variables that are correlated both with innovation and education. We control for many personal traits that could potentially bias our findings. All estimations include robust standard errors. We start with the analysis of having a university degree.

Table 5 presents the estimation results for *r&d* and *mrel* as dependent variable. The first column uses only the dummy variables for education as explanatory variables, the team dummy, the high-tech dummy and the interaction effects. Furthermore, time fixed effects are included to control for potential time trends. The interaction terms can be interpreted as the additional effect of having a certain university degree in one special field and being entrepreneur in the high-tech industry. Having a degree in natural science is weakly significant and positive. In addition, an economics and natural science degree has a positive and statistically significant effect for high-tech entrepreneurs. In the second column all other personal traits are included. It contains sex, nationality, experience, the situation prior to the foundation of the start-up, motives for foundation and ownership structure of the start-up. The last variable is measured by the share of assets that is provided by the entrepreneur himself. It could be that the entrepreneur is more innovative just because of a better financial situation. More equipment can be bought that is used for innovation. The third column includes firm size, the quality of the employment pool and the competition structure. The other regression coefficients are not presented because the education effect on innovation is the focus of this study[3]. As can be seen in all columns, the relation between economics degree and innovation becomes negative and significant. In contrast, for economists in the high-tech industry the effect is significant and positive. The overall net effect is positive for entrepreneurs

[2]The underlying data generating process of the ZEW/KfW Start-Up Panel is random.

[3]Additional regression results can be provided upon request.

engaging in the high-tech industry. This effect seems to be robust among all specifications. Furthermore, we do not find a 'nerd effect'. Having an engineering degree leads to more innovation in the high-tech industry but this effect is only weakly significant (and the only effect among the specifications). Therefore, our initial hypothesis is rejected. Now we interpret columns four to six, which use *mrel* as dependent variable instead of *r&d*. This variable can be interpreted as the output variable of the innovation process. The columns have the same structure as before in the sense that further control variables are included in each step to control for potential biases. As a result, almost all education variables for start-ups in the non-high-tech industry are insignificant. The only specification where a significant result emerges is column four. Natural science exhibits a weakly significant positive effects. An economics and engineering degree in the high-tech industry leads to higher innovation. However, this is not true when personal traits or firm characteristics are included as control variables. Now, it is interesting to investigate whether these effects are also true for practical education. Equations (1) and (2) are re-estimated for persons with apprenticeship as highest education.

The results are completely different, as Table 6 illustrates. Technical education has either no effect or a significant negative influence on innovation activity. Furthermore, social eduction in the high-tech industry is associated with less r&d activity and less introduction of market products. All other education variables are mostly insignificant. The education effect seems even weaker when using *mrel* as dependent variable. All in all, there seems to be neither a 'nerd effect'for entrepreneurs with university degree nor with practical education. For entrepreneurs with a university degree an economics degree can increase innovation as some specifications suggest, while there is no effect for practical education. As argued before, the defined innovation variables are not able to capture the complete innovation process. That is why the following robustness checks with alternative estimation methods and other dependent variables investigate whether the findings depend on the underlying definitions.

4.2 Robustness Checks

The linear probability model approach has the drawback that fitted values of the dependent variable can be outside the range between zero and one. That is why in the following some robustness checks are conducted. Equations (1) and (2) can also be estimated with probit instead of OLS. This guarantees that the fitted values can be interpreted as probabilities. We do not provide the results here but significance levels and signs do not change. Fitted values from our OLS regressions show that only very few values are outside the range between zero and one. This could be a possible explanation why almost the same findings appear.

For further robustness checks, OLS is in the following used. Therefore, further measures are employed. As other input variable, which exhibits a metric scale, R&D expenditures per employee is typically used. They can be interpreted as importance of R&D in the firm. Furthermore, *new* provides information about the innovation level on an ordinal scale with higher values indicating more scope (whether the innovation is only regional or worldwide). An ordered probit approach is used for evaluation. Table 7 reports the results for a university degree.

Almost all specifications are characterized by insignificant education variables for *expend*. Therefore, education does not seem to play an important role for r&d expenditures per employee. *new* shows a positive and significant influence of mathematics/informatics on the scope of the innovation. In contrast, the additional effect of this studid field in the high-tech industry is negative. Again, our hypothesis can be rejected. Table 8 shows the results for practical education. Again, most educational variables become insignificant. Technical education is significant only in column four with negative sign.

pat_ use includes a time dimension showing whether patents today or in future play a role for the start-up. The outcome of this dependent variable can be directly compared with the results of Toivanen and Väänänen (2011). The only difference is that the authors do not concentrate on entrepreneurs but rather investigate innovation activity by all companies. Table 9 shows the regression results for university degree, 10 for practical education. Again OLS is used as for the baseline regressions. A different picture emerges now. Having a degree in economics or natural science in the high-tech industry is associated with more patent use. The signficance of econonomics is larger, while the magnitude of natural is slightly stronger. In contrast, all education variables are insignificant for practical education. The last two variables *prod* and *proc* distinguish between the type of innovation that is conducted. One can think about the possibility that different types of entrepreneurs focus on different aspects of innovation. Table 11 shows the comparison of product and process innovation for entrepreneurs with university degree.

Neither economists nor the technical fields seem to focus more on product or process innovation because there is no effect in the high-tech industry. Table 12 presents the findings for practical education. Many variables are insignificant. Only other services for product innovation and social science in the high-tech industry for process innovation show positive and significant results. All our findings using different proxies for innovation show that the results vary with the underlying definition of innovation. This seems reasonable because the definitions can only illustrate some part of the whole innovation process. Every indicator focuses on different dimensions that are not identical. Nevertheless, one central finding is observed among all specifications: entrepreneurs with practical education do not seem to have a comparative advantage in the high-tech industry compared to economists. Therefore, we do not find a 'nerd effect'in our sample.

5 Conclusion

This paper investigates whether entrepreneurs with technical education in the high-tech industry are more innovative than economists. Policy makers are interested in fostering economic growth and employment. Therefore, it is important to know how to boost innovation in an effective way. The results for the ZEW/KfW Start-Up Panel suggest that there is no 'nerd effect', neither for entrepreneurs with university degree nor for entrepreneurs with practical education. There is a positive effect on innovation for individuals with a university economics degree in the high-tech industry. It can be interpreted as being more able to conduct R&D and sell the innovation to the market. These conclusions cannot be drawn for persons with practical education. In general, the results do not imply that technical education is unimportant. Toivanen and Väänänen (2011) show in their empirical analysis that people with an engineering degree have a higher probability to register a patent compared to others. The channel through which economic growth is fostered seems to be different for engineers as entrepreneurs. It is probably the case that these people self select into research and development units of large companies and contribute there to innovating output. This is not the focus of the study here because we are not able to identify the type of education for employees, only the amount. Robustness checks with other proxies for innovation are conducted to capture more dimensions of the whole innovation process. The definition of innovation influences the results. Nevertheless, the central conclusion that there is no 'nerd effect'is maintained.

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Appendix

High-technology industries
Cutting-edge technology manufacturing
High-technology manufacturing
Technology-intensive services
Software
Non-high-tech industries
Non-high-tech manufacturing
Skill-intensive services (non-technical, consulting services)
Other business-oriented services
Consumer-oriented services
Construction
Wholesale and retail market

Table 1: Industry classifications

Variable	Obs	Mean	Std. Dev.	1%	99%
r&d	7,028	0.2314	0.4217	0	1
mrel	7,028	0.2107	0.4079	0	1
expend	7,028	2,920.89	20,910.88	0	50,000
new	7,028	1.39	0.8353	1	4
pat_use	5,006	0.0759	0.2649	0	1
prod	4,048	0.3752	0.4842	0	1
proc	4,077	0.2727	0.4454	0	1

Table 2: Summary statistics of dependent variables (innovation)

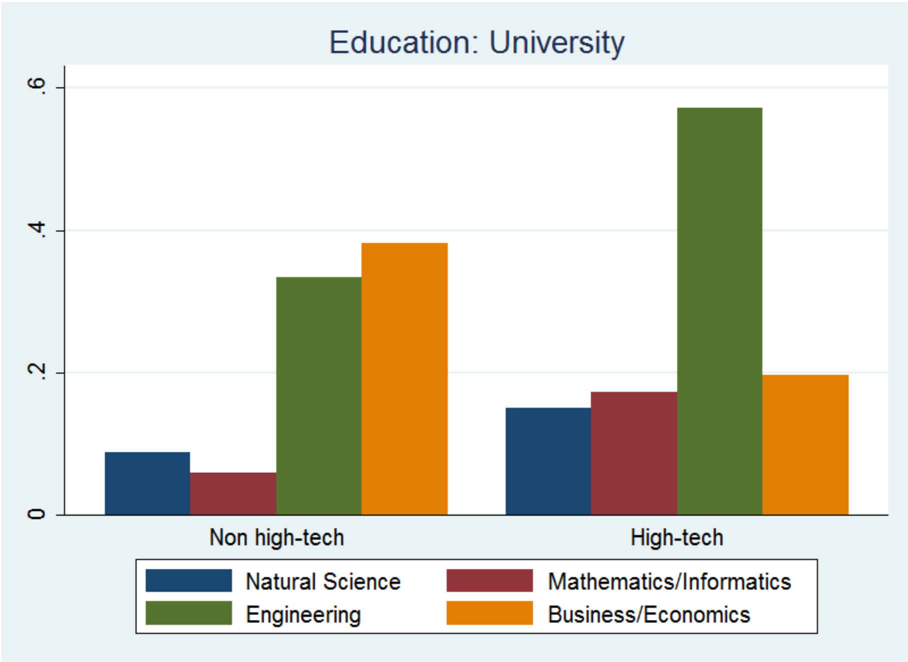

Figure 1: Share of education (university) in non high-tech and high-tech industries

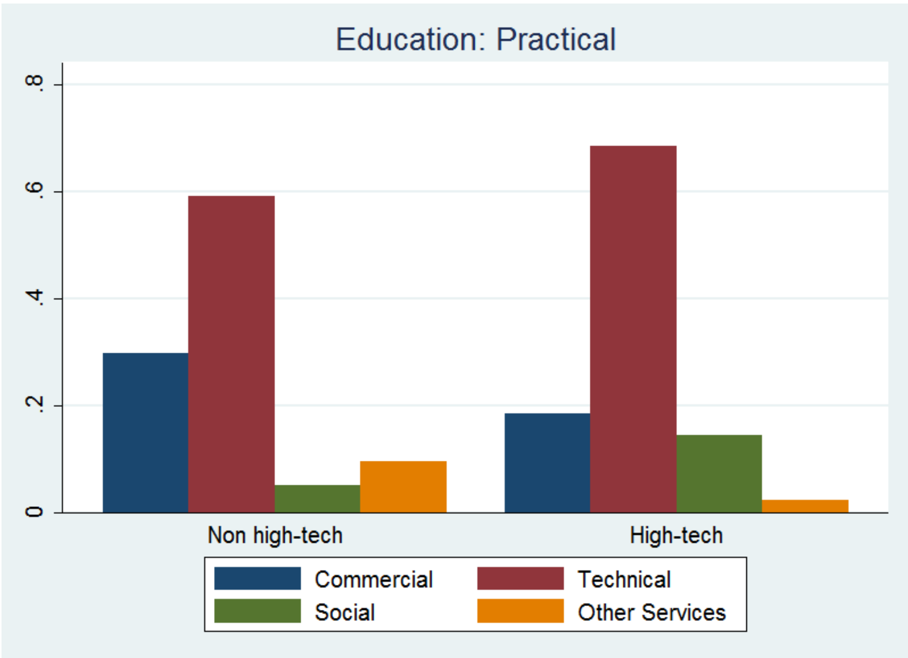

Figure 2: Share of education (practical) in non high-tech and high-tech industries

Variable	Obs	Mean	Std. Dev.	1%	99%
A. Education					
uni	7,028	0.3840	0.4864	0	1
nat	2,660	0.1218	0.3271	0	1
mathinf	2,660	0.1214	0.3267	0	1
eng	2,660	0.4654	0.4989	0	1
econ	2,660	0.2789	0.4486	0	1
other	2,660	0.1526	0.3597	0	1
comm	4,493	0.2597	0.4385	0	1
tech	4,493	0.6227	0.4848	0	1
social	4,493	0.0828	0.2756	0	1
othserv	4,493	0.0701	0.2554	0	1
other_job	4,493	0.0445	0.2063	0	1
B. Other personal traits					
ger	7,020	0.9352	0.2462	0	1
male	7,028	0.8029	0.3978	0	1
sit_e	7,007	0.2179	0.4129	0	1
sit_em	7,007	0.6158	0.4864	0	1
sit_unem	7,007	0.1590	0.3657	0	1
sit_ne	7,007	0.0918	0.2887	0	1
C. Firm characteristics					
ht	7,028	0.4119	0.4922	0	1
team	7,028	0.2694	0.4437	0	1
fin_sh	4,745	20.66	30.72	0	100
fin_ext_sh	4,820	12.49	25.49	0	100
employment	7,028	4.64	6.61	1	29
sh_l	6,013	0.8202	2.97	0	14
sh_m	6,016	1.63	3.44	0	16
sh_h	6,020	0.3802	1.65	0	8
lcomp	4,886	0.2386	0.4263	0	1
mcomp	4,886	0.2016	0.4012	0	1
hcomp	4,886	0.5598	0.4965	0	1

Table 3: Summary statistics of explanatory variables

Variable	r&d	mrel	expend	new	pat_use	prod	proc
r&d	1.0000						
mrel	0.3022	1.0000					
expend	0.2595	0.0998	1.0000				
new	0.3570	0.9009	0.1418	1.0000			
pat_use	0.3178	0.2609	0.2000	0.3369	1.0000		
prod	0.2480	0.2618	0.0299	0.2520	0.0988	1.0000	
proc	0.2357	0.1877	0.0579	0.1927	0.1198	0.3715	1.0000

Table 4: Correlation matrix

Variables	r&d	r&d	r&d	mrel	mrel	mrel
team	0.0947***	0.0283	0.0122	0.0872***	0.0306	0.0126
	(0.0187)	(0.0269)	(0.0265)	(0.0184)	(0.0260)	(0.0256)
ht	0.102**	0.0961*	0.0839	-0.0140	-0.0334	-0.00222
	(0.0438)	(0.0545)	(0.0533)	(0.0426)	(0.0520)	(0.0507)
nat	0.0932*	0.0636	0.0341	0.0904*	0.0576	0.0396
	(0.0503)	(0.0640)	(0.0607)	(0.0515)	(0.0660)	(0.0625)
mathinf	0.0492	0.0527	0.0292	0.0770	0.0882	0.0971
	(0.0574)	(0.0703)	(0.0678)	(0.0586)	(0.0703)	(0.0719)
eng	-0.0184	-0.0424	-0.0441	-0.0421	-0.0541	-0.0308
	(0.0325)	(0.0419)	(0.0415)	(0.0317)	(0.0408)	(0.0398)
econ	-0.0448	-0.0701*	-0.0856**	-0.0116	-0.0337	-0.0239
	(0.0310)	(0.0397)	(0.0390)	(0.0312)	(0.0404)	(0.0399)
ht_nat	0.120*	0.139*	0.115	0.0572	0.0823	0.0695
	(0.0652)	(0.0827)	(0.0794)	(0.0660)	(0.0832)	(0.0797)
ht_mathinf	0.0555	0.0599	0.0785	-0.0745	-0.0995	-0.113
	(0.0704)	(0.0858)	(0.0830)	(0.0703)	(0.0839)	(0.0846)
ht_eng	0.0545	0.0846	0.0821	0.0862*	0.0950	0.0629
	(0.0483)	(0.0598)	(0.0590)	(0.0471)	(0.0578)	(0.0563)
ht_econ	0.171***	0.152**	0.147**	0.0986**	0.0843	0.0574
	(0.0482)	(0.0602)	(0.0591)	(0.0477)	(0.0598)	(0.0581)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Entr. Char.	No	Yes	Yes	No	Yes	Yes
Firm Char.	No	No	Yes	No	No	Yes
Observations	2,660	1,673	1,643	2,660	1,673	1,643
R-squared	0.088	0.160	0.204	0.028	0.093	0.156

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Baseline regressions for university degree. Standard errors are corrected for heteroscedasticity.

Variables	r&d	r&d	r&d	mrel	mrel	mrel
team	0.114***	0.0816***	0.0624***	0.0967***	0.0483**	0.0332
	(0.0147)	(0.0214)	(0.0213)	(0.0150)	(0.0210)	(0.0213)
ht	0.278***	0.252***	0.237***	0.0917*	0.0880	0.0806
	(0.0491)	(0.0616)	(0.0605)	(0.0495)	(0.0606)	(0.0579)
comm	-0.00471	-0.00164	-0.00755	-0.0115	-0.00294	-0.00313
	(0.0220)	(0.0297)	(0.0291)	(0.0240)	(0.0319)	(0.0321)
tech	0.00557	0.000194	0.00673	-0.0593**	-0.0396	-0.0273
	(0.0221)	(0.0305)	(0.0301)	(0.0241)	(0.0318)	(0.0318)
social	-0.0528*	-0.0402	-0.0467	-0.0204	0.0101	-0.00227
	(0.0270)	(0.0396)	(0.0397)	(0.0345)	(0.0473)	(0.0497)
othserv	0.0358	0.0672*	0.0486	-0.00834	-0.000668	-0.0260
	(0.0278)	(0.0387)	(0.0393)	(0.0307)	(0.0404)	(0.0414)
ht_comm	-0.0190	-0.0448	-0.0513	-0.00745	-0.0109	-0.0238
	(0.0474)	(0.0603)	(0.0588)	(0.0478)	(0.0606)	(0.0578)
ht_tech	-0.147***	-0.133**	-0.116*	-0.0145	-0.0268	-0.0144
	(0.0488)	(0.0615)	(0.0602)	(0.0488)	(0.0601)	(0.0575)
ht_social	-0.175***	-0.179**	-0.149**	-0.0985*	-0.117	-0.0732
	(0.0543)	(0.0715)	(0.0713)	(0.0589)	(0.0733)	(0.0729)
ht_othserv	-0.0428	0.00674	0.0429	0.0969	0.167	0.207*
	(0.0940)	(0.117)	(0.117)	(0.0957)	(0.123)	(0.119)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Entr. Char.	No	Yes	Yes	No	Yes	Yes
Firm Char.	No	No	Yes	No	No	Yes
Observations	4,493	2,870	2,798	4,493	2,870	2,798
R-squared	0.069	0.085	0.127	0.026	0.067	0.105

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Baseline regressions for practical education. Standard errors are corrected for heteroscedasticity.

Variables	expend	expend	expend	new	new	new
team	-359.2	-627.7	-673.9	0.270***	0.122	0.0691
	(1,080)	(1,008)	(1,026)	(0.0519)	(0.0772)	(0.0804)
ht	3,540	2,574	2,322	0.0747	-0.0254	0.0468
	(2,543)	(2,477)	(2,483)	(0.121)	(0.150)	(0.158)
nat	3,089*	1,449	514.8	0.281**	0.225	0.154
	(1,601)	(1,056)	(998.1)	(0.132)	(0.167)	(0.170)
mathinf	2,020	2,906	2,341	0.335**	0.393**	0.456**
	(1,402)	(1,917)	(1,959)	(0.162)	(0.200)	(0.214)
eng	431.2	-167.9	-111.6	-0.0630	-0.116	-0.0547
	(584.2)	(620.8)	(647.9)	(0.0960)	(0.122)	(0.128)
econ	443.3	583.1	370.1	0.00328	-0.0592	-0.0499
	(642.3)	(734.2)	(744.6)	(0.0905)	(0.116)	(0.125)
ht_nat	2,251	3,386	2,767	0.172	0.251	0.240
	(2,835)	(2,410)	(2,387)	(0.172)	(0.220)	(0.223)
ht_mathinf	-3,040	-3,669	-3,441	-0.327*	-0.409*	-0.492*
	(2,857)	(2,652)	(2,671)	(0.194)	(0.240)	(0.255)
ht_eng	274.2	1,335	938.7	0.195	0.278	0.198
	(2,723)	(2,604)	(2,650)	(0.136)	(0.169)	(0.177)
ht_econ	6,016*	2,049	1,901	0.215*	0.190	0.123
	(3,498)	(3,065)	(3,099)	(0.130)	(0.169)	(0.178)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Entr. Char.	No	Yes	Yes	No	Yes	Yes
Firm Char.	No	No	Yes	No	No	Yes
Observations	2,660	1,673	1,643	2,660	1,673	1,643
R-squared	0.022	0.052	0.085			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: OLS and ordered probit regressions for university degree. Standard errors are corrected for heteroscedasticity.

Variables	expend	expend	expend	new	new	new
team	900.9**	1,094*	1,124*	0.393***	0.214***	0.179**
	(449.9)	(633.7)	(657.4)	(0.0494)	(0.0731)	(0.0762)
ht	2,256*	1,690	1,497	0.384**	0.395**	0.403**
	(1,350)	(1,506)	(1,538)	(0.160)	(0.201)	(0.201)
comm	-635.3	92.64	279.9	0.0121	0.0708	0.0801
	(670.4)	(978.6)	(1,027)	(0.0894)	(0.119)	(0.125)
tech	-594.2	-999.4	-927.2	-0.198**	-0.108	-0.0592
	(683.1)	(825.9)	(861.5)	(0.0896)	(0.119)	(0.123)
social	1,800	4,679	4,553	-0.0867	0.0465	0.0337
	(2,970)	(5,146)	(5,177)	(0.132)	(0.180)	(0.193)
othserv	-591.6	-1,213	-1,229	-0.0463	-0.0227	-0.126
	(953.5)	(896.8)	(918.7)	(0.110)	(0.146)	(0.158)
ht_comm	1,204	-64.23	-216.7	-0.0658	-0.105	-0.179
	(1,234)	(1,468)	(1,478)	(0.158)	(0.202)	(0.202)
ht_tech	-979.6	-385.4	-270.2	-0.0205	-0.0917	-0.0800
	(1,374)	(1,530)	(1,557)	(0.161)	(0.201)	(0.201)
ht_social	-4,512	-6,619	-6,173	-0.351*	-0.465*	-0.361
	(3,153)	(5,357)	(5,334)	(0.205)	(0.262)	(0.268)
ht_othserv	-1,565	-359.6	-402.0	0.227	0.374	0.527*
	(1,634)	(1,458)	(1,533)	(0.258)	(0.304)	(0.295)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Entr. Char.	No	Yes	Yes	No	Yes	Yes
Firm Char.	No	No	Yes	No	No	Yes
Observations	4,493	2,870	2,798	4,493	2,870	2,798
R-squared	0.004	0.012	0.018			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: OLS and ordered probit regressions for practical education. Standard errors are corrected for heteroscedasticity.

Variables	pat_use	pat_use	pat_use
team	0.0533***	0.0229	0.0218
	(0.0158)	(0.0187)	(0.0190)
ht	-0.0106	-0.00379	-0.00460
	(0.0364)	(0.0385)	(0.0382)
nat	0.0894**	0.0788	0.0570
	(0.0448)	(0.0499)	(0.0479)
mathinf	-0.0561**	-0.0515*	-0.0629***
	(0.0240)	(0.0271)	(0.0244)
eng	0.0140	0.00457	0.00647
	(0.0226)	(0.0261)	(0.0266)
econ	-0.00343	-0.0195	-0.0208
	(0.0221)	(0.0241)	(0.0240)
ht_nat	0.135**	0.134**	0.130*
	(0.0636)	(0.0674)	(0.0663)
ht_mathinf	0.0617	0.0607	0.0658
	(0.0419)	(0.0443)	(0.0424)
ht_eng	0.0736*	0.0641	0.0557
	(0.0405)	(0.0425)	(0.0428)
ht_econ	0.128***	0.126***	0.120***
	(0.0436)	(0.0449)	(0.0452)
Time Effects	Yes	Yes	Yes
Entr. Char.	No	Yes	Yes
Firm Char.	No	No	Yes
Observations	1,844	1,673	1,643
R-squared	0.065	0.107	0.128

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: OLS regressions for university degree. Standard errors are corrected for heteroscedasticity.

Variables	pat_use	pat_use	pat_use
team	0.0460***	0.0199	0.0177
	(0.0109)	(0.0131)	(0.0134)
ht	0.0828**	0.0773*	0.0658
	(0.0412)	(0.0422)	(0.0420)
comm	0.00775	0.0131	0.0135
	(0.0146)	(0.0170)	(0.0176)
tech	4.52e-05	0.00834	0.00885
	(0.0150)	(0.0175)	(0.0182)
social	-0.0190	-0.00576	-0.0123
	(0.0182)	(0.0216)	(0.0220)
othserv	-0.0102	-0.0117	-0.0233
	(0.0166)	(0.0176)	(0.0188)
ht_comm	0.0273	0.0261	0.0250
	(0.0414)	(0.0427)	(0.0428)
ht_tech	-0.0410	-0.0377	-0.0270
	(0.0414)	(0.0423)	(0.0422)
ht_social	-0.0483	-0.0426	-0.0217
	(0.0454)	(0.0469)	(0.0471)
ht_othserv	-0.0306	-0.0406	-0.0194
	(0.0604)	(0.0535)	(0.0548)
Time Effects	Yes	Yes	Yes
Entr. Char.	No	Yes	Yes
Firm Char.	No	No	Yes
Observations	3,251	2,870	2,798
R-squared	0.029	0.054	0.071

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: OLS regressions for practical education. Standard errors are corrected for heteroscedasticity.

Variables	prod	prod	prod	proc	proc	proc
team	0.0609**	0.0307	0.0126	0.0722***	0.0248	0.00547
	(0.0267)	(0.0364)	(0.0373)	(0.0251)	(0.0347)	(0.0348)
ht	0.0757	0.141*	0.145**	0.0707	0.111*	0.122*
	(0.0615)	(0.0729)	(0.0731)	(0.0567)	(0.0668)	(0.0668)
nat	-0.0256	0.0116	-0.00285	0.0473	0.0402	0.0355
	(0.0738)	(0.0870)	(0.0879)	(0.0692)	(0.0804)	(0.0821)
mathinf	-0.0199	0.0125	0.00923	0.0342	0.0972	0.0804
	(0.0828)	(0.0916)	(0.0962)	(0.0757)	(0.0893)	(0.0927)
eng	-0.0625	-0.0182	-0.0255	-0.0197	0.00777	-0.000867
	(0.0474)	(0.0554)	(0.0565)	(0.0409)	(0.0492)	(0.0499)
econ	-0.0365	-0.00959	-0.0214	0.0281	0.0512	0.0348
	(0.0470)	(0.0547)	(0.0555)	(0.0416)	(0.0495)	(0.0504)
ht_nat	0.0621	-0.0139	-0.00933	-0.00601	-0.0589	-0.0824
	(0.0932)	(0.111)	(0.111)	(0.0881)	(0.103)	(0.103)
ht_mathinf	-0.0728	-0.120	-0.114	-0.0554	-0.137	-0.136
	(0.100)	(0.112)	(0.115)	(0.0933)	(0.108)	(0.110)
ht_eng	-0.0107	-0.0858	-0.0871	0.0292	-0.00680	-0.0134
	(0.0684)	(0.0811)	(0.0811)	(0.0625)	(0.0741)	(0.0738)
ht_econ	0.104	0.0276	0.0293	0.126*	0.0649	0.0457
	(0.0692)	(0.0825)	(0.0827)	(0.0647)	(0.0758)	(0.0758)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Entr. Char.	No	Yes	Yes	No	Yes	Yes
Firm Char.	No	No	Yes	No	No	Yes
Observations	1,522	1,129	1,114	1,531	1,134	1,119
R-squared	0.019	0.046	0.067	0.031	0.046	0.074

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11: OLS regressions for university degree. Standard errors are corrected for heteroscedasticity.

Variables	prod	prod	prod	proc	proc	proc
team	0.0813***	0.0706**	0.0530*	0.113***	0.0991***	0.0786***
	(0.0230)	(0.0307)	(0.0314)	(0.0217)	(0.0289)	(0.0297)
ht	0.103	0.177**	0.171**	0.0628	-0.0128	-0.0534
	(0.0727)	(0.0853)	(0.0836)	(0.0654)	(0.0756)	(0.0760)
comm	0.0353	0.0612	0.0593	-0.00352	0.0135	-0.00533
	(0.0372)	(0.0427)	(0.0436)	(0.0330)	(0.0382)	(0.0379)
tech	-0.0395	-0.00514	0.0114	-0.0354	-0.0377	-0.0426
	(0.0371)	(0.0428)	(0.0440)	(0.0328)	(0.0388)	(0.0389)
social	0.00520	-0.0144	-0.0144	0.00767	-0.00808	-0.0294
	(0.0592)	(0.0670)	(0.0674)	(0.0531)	(0.0621)	(0.0613)
othserv	0.146***	0.174***	0.141**	0.00506	0.0113	-0.00528
	(0.0499)	(0.0594)	(0.0614)	(0.0432)	(0.0521)	(0.0521)
ht_comm	0.0251	-0.0580	-0.0590	0.0447	0.0530	0.0629
	(0.0711)	(0.0848)	(0.0834)	(0.0654)	(0.0773)	(0.0771)
ht_tech	-0.0246	-0.105	-0.103	0.00128	0.0763	0.110
	(0.0727)	(0.0850)	(0.0834)	(0.0658)	(0.0764)	(0.0762)
ht_social	-0.00223	0.00232	0.0202	0.0894	0.176*	0.230**
	(0.0915)	(0.107)	(0.105)	(0.0839)	(0.0993)	(0.100)
ht_othserv	-0.0638	-0.228	-0.180	-0.00106	-0.000291	0.0383
	(0.124)	(0.157)	(0.148)	(0.117)	(0.140)	(0.146)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Entr. Char.	No	Yes	Yes	No	Yes	Yes
Firm Char.	No	No	Yes	No	No	Yes
Observations	2,632	1,954	1,901	2,653	1,968	1,911
R-squared	0.027	0.044	0.066	0.030	0.045	0.067

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: OLS regressions for practical education. Standard errors are corrected for heteroscedasticity.