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

Stefan Goldbach

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Stefan Goldbach[*][†]

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Abstract

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 2005 and 2007 is used. Two independent OLS regressions are conducted for entrepreneurs with university degree and practical 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'. The results depend on the underlying definition of innovation, as robustness checks show.

Keywords: entrepreneurship, innovation, education
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[*]Address: Chair of International Economics, Darmstadt University of Technology, Marktplatz 15, 64283 Darmstadt, goldbach@vwl.tu.darmstadt.de

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1 Introduction

Western countries pay workers higher wages on average compared to the rest of the world and rely on innovative products for economic growth (Hasan and Tucci (2010)). Another important factor for economic growth that is mentioned by governments 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 always 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. Gilbert and Newbery (1982) argue that companies can register a patent without ever using it. 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. The authors focus more on invention which is closely related to innovation in general. They conclude that persons with an engineering background have a positive effect on invention. However, the authors do not distinguish between different types of firms. The traditional entrepreneurship literature emphasizes the role of large co-operations in the innovation process. According to this, 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: are entrepreneurs with technical education more innovative in high-tech industries compared to economists? To analyze this question, the KfW/ZEW Start-Up Panel is used. It contains a random sample of German start-up companies between 2005 and 2007. Two independent OLS regressions are conducted for entrepreneurs with university degree and practical 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'. Nevertheless, the results highly depend on the underlying definition of innovation.

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

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. Furthermore, more schooling also leads directly to more profitability.

Davidsson and Honig (2003) examine whether and how human and social capital are able to explain the entry decision and the 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. Furthermore, 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 results 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).
Nevertheless, there are empirical contributions that test the hypothesis for other countries. One 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. Toivanen and Väänänen (2011) investigate whether an engineering degree has an influence on the registration of patents. The authors focus more on invention which is closely related to innovation in general. 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 and are more able to fix possible problems. That is why we want to test the following hypothesis

Hypothesis 1 *Entrepreneurs with technical education (natural science, math-*

ematics/informatics, engineering) have a comparative advantage in high-tech industries compared to entrepreneurs with an economics degree.

3 Data and Summary Statistics

The data used in this analysis 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 random sample and contains yearly data for German start-up companies between 2005 and 2007. Further information is provided by Fryges et al. (2010). It was generated by telephone interviews. Therefore, the variables are all self-reported. An entrepreneur is defined here as someone who belongs to the persons establishing a start-up. However, one person can have more than one degree. In a first step, the variables that are used in this paper are defined.

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. Typically input and output variables are used in empirical studies. There are some attempts, according to Acs and Audretsch (2005), to measure innovation more accurately by using independent experts in the technological field who are able to weight the innovations. Having potential problems of measuring innovation in mind, I approximate innovation 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 on the market has been released since the foundation (*mrel*) are used. For robustness checks, R&D expenditures per worker (*exp*), 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. The main explanatory variable in this analysis is education. Education is measured in two dimensions: the amount is measured by the dummy variables *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 subject that is studied. Dummy variables are used for business or economics (*econ*), natural science (*nat*), mathematics or informatics (*mathinf*), engineering (*eng*) and other subjects (*other*). These dummy variables are only available for entrepreneurs with a university degree. The subjects for individuals with practical education have a different notation. Having an apprenticeship in commerce is *comm*. The other subjects 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, main reason for foundation and ownership are included. Experience is measured in intervals: less than seven years (*exp7*), more than seven and less than 13 years (*exp713*), more than 13 and less than 20 years (*exp1320*) and more than 20 years (*exp20*). The employment situation immediately before the start of the venture is measured as follows: an entrepreneur was either self-employed (*sit_e*), employed (*sit_em*), unemployed (*sit_unem*) or not working (*sit_ne*). Two dummy variables are included as main reason for becoming an entrepreneur: a dummy variable for working independently (*self*) or implementing an idea (*idea*). Ownership is measured by the share that is financed by the entrepreneur himself (*fin_sh*) and by 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 (*full*), part time (*part*), mini (*mini*), family members (*fam*), trainees (*trainee*), freelancer (*free*), interns (*intern*) and temporary employees (*temp*). 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. Another factor influencing innovating behaviour is the competition structure. *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 analysis. The classification is described in the next table.

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

3.3 Summary Statistics

This subsection starts with the provision of some stylized facts based on the the sample. Table 2 provides a description for personal traits, table 3 for firm characteristics. These summary statistics are for the whole data set.

Seven variables are approximated for the innovation process which are used as dependent variables later on. The first indicator shows that 20% of the start-ups are temporarily or permanently engaged in R&D. Furthermore, 18% have released a market innovation since foundation. These two variables only illustrate a small part of the whole innovation process. That is why other

Variable	Obs	Mean	Std. Dev.	1%	99%
nat	1052	0.0922	0.2895	0	1
mathinf	1052	0.1065	0.3086	0	1
eng	1052	0.4696	0.4993	0	1
econ	1052	0.2091	0.4069	0	1
other	1052	0.1397	0.3469	0	1
comm	2503	0.2273	0.4192	0	1
tech	2503	0.6272	0.4836	0	1
social	2503	0.0710	0.2571	0	1
othserv	2503	0.0727	0.2597	0	1
other_job	2503	0.0412	0.1987	0	1
ht	3718	0.3682	0.4824	0	1
uni	3718	0.2873	0.4525	0	1
german	3715	0.9219	0.2683	0	1
male	3718	0.8453	0.3616	0	1
exp713	3718	0.2501	0.4331	0	1
exp1320	3718	0.2813	0.4497	0	1
exp20	3718	0.1937	0.3952	0	1
sit_e	3706	0.1206	0.3257	0	1
sit_em	3706	0.5828	0.4932	0	1
sit_unem	3706	0.2094	0.4069	0	1
self	3530	0.4844	0.4998	0	1
idea	3530	0.2462	0.4308	0	1
fin_sh	3503	20.0425	30.1621	0	100
fin_ext_sh	3559	11.7631	24.7012	0	100

Table 2: Summary statistics of personal traits

variables are included that can illustrate further aspects. The variables *new* and *exp* are on a metric scale and cannot be interpreted in a proper way. Pat_use indicates that only a small fraction of start-ups (approximately 5%) are engaged today or in future in patenting. 35% of start-up innovations are connected to products, 24% exhibit innovation in processes. Turning, now, to the education variables in the sample: approximately 30% have a university degree. From these, 47% studied engineering, 21% economics, 11% mathematics or informatics, 9% natural science and 12% another subject. As a result, most start-ups in the sample were founded by persons with

Variable	Obs	Mean	Std. Dev.	1%	99%
r&d	3718	0.2023	0.4018	0	1
mrel	3718	0.1762	0.3810	0	1
exp	2149	2042.52	10593.92	0	50000
new	3718	1.2985	0.7207	1	4
pat_use	3718	0.0551	0.2283	0	1
prod	2539	0.3478	0.4764	0	1
proc	2563	0.2407	0.4276	0	1
full	3689	1.0507	2.9940	0	14
part	3687	0.2729	0.9986	0	4
mini	3688	0.5973	2.7904	0	7
fam	3688	0.2253	0.5910	0	3
trainee	3687	0.1098	0.4452	0	2
free	3685	0.3800	2.3980	0	6
intern	3684	0.0912	0.3862	0	2
temp	3683	0.0665	0.9837	0	2
employment	3676	2.7318	5.2283	0	24
sh_m	3689	1.2223	2.8251	0	14
sh_h	3683	0.1988	1.1818	0	5
mcomp	3622	0.1971	0.3979	0	1
hcomp	3622	0.5834	0.4931	0	1

Table 3: Summary statistics of firm characteristics

technical background. These numbers are compared with individuals who have a practical education: most have either a technical (63%) or commercial (23%) education. 37% of start-ups are engaged in the high-tech industry. 85% of the entrepreneurs are male, 95% are German. Experience is almost equally distributed among the four intervals. Most entrepreneurs (58%) were employed in a firm prior to the start-up. The mean entrepreneur contributes 20% of the assets by himself and receives 11% from outside financiers. Many start-ups have only few employees (2-3) and, if so, the share with practical education is highest. 58% face high competition in their field. To obtain further insight, Tables 4 and 5 show the distribution of the same variables, now for non-hightech start-ups.

For the non-high-tech firms only 14% of the start-ups are temporarily or permanently engaged in R&D. A market innovation is released by 15%.

Variable	Obs	Mean	Std. Dev.	1%	99%
nat	505	0.0851	0.2794	0	1
mathinf	505	0.0455	0.2087	0	1
eng	505	0.3465	0.4763	0	1
econ	505	0.3030	0.4600	0	1
other	505	0.2317	0.4223	0	1
comm	1756	0.2597	0.4386	0	1
tech	1756	0.6025	0.4895	0	1
social	1756	0.0438	0.2048	0	1
othserv	1756	0.0951	0.2934	0	1
other_job	1756	0.0456	0.2086	0	1
uni	2349	0.2197	0.4141	0	1
male	2349	0.8003	0.3998	0	1
german	2349	0.9149	0.2792	0	1
exp713	2349	0.2354	0.4244	0	1
exp1320	2349	0.2737	0.4460	0	1
exp20	2349	0.1997	0.3998	0	1
sit_e	2341	0.1128	0.3164	0	1
sit_em	2341	0.5856	0.4927	0	1
sit_unem	2341	0.2290	0.4203	0	1
self	2227	0.4809	0.4997	0	1
idea	2227	0.2366	0.4251	0	1
fin_sh	2180	18.8982	28.6906	0	100
fin_ext_sh	2216	14.4129	27.1114	0	100

Table 4: Summary statistics for personal traits of non-high-tech start-ups

Fewer firms engage in patenting, product and process innovation. All statistics indicate that non-high-tech firms are overall less innovative according to all proposed definitions. What does the distribution of education in this subsample look like? 20% hold a university degree. Of these, 35% studied engineering, 30% economics, 5% mathematics or informatics, 9% natural science and 23% another subject. Compared to the whole distribution, economics and other subjects are better represented than the technical fields. For practical education, a similar distribution as for the whole sample emerges. The fraction of male entrepreneurs is lower (80%) but the share of Germans remains constant. Experience is again approximately equally distributed. The

Variable	Obs	Mean	Std. Dev.	1%	99%
r&d	2349	0.1392	0.3462	0	1
mrel	2349	0.1486	0.3557	0	1
exp	1448	566.15	4181.09	0	18000
new	2349	1.2320	0.6207	1	4
pat_use	2349	0.0366	0.1878	0	1
prod	1585	0.3085	0.4620	0	1
proc	1598	0.1990	0.3994	0	1
full	2328	1.2049	3.2377	0	14
part	2326	0.3315	1.1705	0	4
mini	2326	0.7524	3.4403	0	8
fam	2327	0.2325	0.5781	0	3
trainee	2326	0.1363	0.4976	0	2
free	2323	0.3065	2.4460	0	5
intern	2323	0.0921	0.3884	0	2
temp	2322	0.0831	1.2000	0	2
employment	2315	3.0436	5.7132	0	24
sh_m	2326	1.4368	3.1245	0	15
sh_h	2321	0.0913	0.6055	0	3
mcomp	2289	0.2145	0.4106	0	1
hcomp	2289	0.5627	0.4962	0	1

Table 5: Summary statistics for firm characteristics of non-high-tech start-ups

fraction of entrepreneurs that were self-employed is almost the same as before. The mean entrepreneur contributes less by himself and receives more external finance. The start-ups are characterized by more employees and a higher share of low-educated and lower share of high-educated individuals. Less firms face high competition.

Finally, high-tech firms are described in more detail. As expected, they (31%) invest more in R&D. The share of companies providing a market innovation is also higher (22%). Patents seem to be more important and more product and process innovations are conducted. The same is true for the number of patents and the proportion of start-ups that registered a patent. Consequently, start-ups in the high-tech industry are more innovative than other firms. 40% have a university degree as highest education. Of these,

Variable	Obs	Mean	Std. Dev.	1%	99%
nat	547	0.0987	0.2986	0	1
mathinf	547	0.1627	0.3694	0	1
eng	547	0.5831	0.4935	0	1
econ	547	0.1225	0.3281	0	1
other	547	0.0548	0.2279	0	1
comm	747	0.1513	0.3586	0	1
tech	747	0.6854	0.4647	0	1
social	747	0.1352	0.3422	0	1
othserv	747	0.0201	0.1404	0	1
other_job	747	0.0308	0.1729	0	1
uni	1369	0.4032	0.4907	0	1
german	1366	0.9341	0.2482	0	1
male	1369	0.9226	0.2674	0	1
exp713	1369	0.2754	0.4469	0	1
exp1320	1369	0.2944	0.4559	0	1
exp20	1369	0.1833	0.3871	0	1
sit_e	1365	0.1341	0.3408	0	1
sit_em	1365	0.5780	0.4941	0	1
sit_unem	1365	0.1758	0.3808	0	1
self	1303	0.4904	0.5001	0	1
idea	1303	0.2625	0.4401	0	1
fin_sh	1323	21.9282	32.3645	0	100
fin_ext_sh	1343	7.3909	19.3330	0	100

Table 6: Summary statistics for personal traits of high-tech start-ups

58% studied engineering, 12% economics, 16% mathematics or informatics, 10% natural science and 5% another subject. This subsample represents a higher share of individuals with technical education. This is also true for practical education. The fraction of male entrepreneurs is higher than before. This represents men's willingness to bear risks. The nationality again remains constant. Most entrepreneurs have experience ranging between 13 and 20 years. The fraction of entrepreneurs that were self-employed is again similar. The mean entrepreneur contributes more by himself and receives less from outside investors. The start-ups are characterized by fewer employees and a higher share of high-educated and lower share of low-educated indi-

Variable	Obs	Mean	Std. Dev.	1%	99%
r&d	1369	0.3104	0.4628	0	1
mrel	1369	0.2235	0.4168	0	1
exp	701	5092.14	17158.96	0	100000
new	1369	1.4127	0.8540	1	4
pat_use	1369	0.0869	0.2818	0	1
prod	954	0.4130	0.4926	0	1
proc	965	0.3098	0.4627	0	1
full	1361	0.7869	2.5021	0	14
part	1361	0.1727	0.5869	0	3
mini	1362	0.3326	0.8743	0	4
fam	1361	0.2131	0.6125	0	3
trainee	1361	0.0647	0.3324	0	2
free	1362	0.5051	2.3094	0	6
intern	1361	0.0900	0.3826	0	2
temp	1361	0.0382	0.4022	0	2
employment	1361	2.2013	4.2285	0	20
sh_m	1363	0.8562	2.1755	0	10
sh_h	1362	0.3818	1.7608	0	8
mcomp	1333	0.1673	0.3734	0	1
hcomp	1333	0.6189	0.4858	0	1

Table 7: Summary statistics of firm characteristics of high-tech start-ups

viduals. High-tech firms face higher competition compared to non-high-tech firms.

4 Empirical Results

4.1 Baseline Regressions

The summary statistics show that there are differences in the dependent and explanatory variables for high-tech and non-high-tech start-ups. However, the effect of the type of education on innovation can only be estimated unbiased if other variables that are correlated with with education are also accounted for in the model. That is why different control variables are included that are possibly correlated with education and innovation. In the baseline regressions, we use *r&d* and *mrel* as dependent variables. They describe different parts of the innovation process. *r&d* can be interpreted as input variables, *mrel* as output variable. Furthermore, other innovation proxies are used for robustness checks. *exp* 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 by more subjective measures) and can be evaluated at a metric scale. For the variable *new* this is only partly true. It is again a metric variable for the innovation output but no objective evaluation. If the variable takes value one, 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 also output variables but also dummies. They concentrate more on the type of innovation. As a consequence, it can be argued that the variables for innovation describe different input and output aspects of the innovation process. Table 8 shows the correlation among the dependent variables.

Variable	r&d	mrel	exp	new	pat_use	prod	proc
r&d	1.0000						
mrel	0.2661	1.0000					
exp	0.3611	0.1228	1.0000				
new	0.3153	0.8952	0.1905	1.0000			
pat_use	0.2902	0.2640	0.3131	0.3219	1.0000		
prod	0.2544	0.2851	0.0648	0.2867	0.1000	1.0000	
proc	0.2536	0.1590	0.1320	0.1748	0.0873	0.3362	1.0000

Table 8: Correlation matrix

The correlation matrix 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

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

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

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 entrepreneur 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. What does the ideal experiment for causal analysis look like in this setting? 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. All estimations include robust standard errors. The reference group for the estimation are entrepreneurs with *other* or *other_job* education, less than seven years of experience *exp7*, not working before *sit_ne* and facing low competition *lcomp*.

We start with the analysis of having a university degree. Table 9 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 high-tech dummy and the interaction effects. Furthermore, two time dummy variables are included that control for possible time effects. The interaction terms can be interpreted as the additional effect of having a certain university degree and being entrepreneur in the high-tech industry. Having an economics degree is weakly significant and negative. In contrast, an eco-

Variables	r&d	r&d	r&d	mrel	mrel	mrel
nat	0.0228	0.0179	-0.00694	0.131	0.106	0.0789
mathinf	0.0964	0.0784	0.0643	-0.0154	-0.0528	-0.0324
eng	-0.0467	-0.0469	-0.0553	-0.0393	-0.0282	-0.00634
econ	-0.0963*	-0.0987*	-0.110**	-0.0568	-0.0484	-0.0282
ht	0.0595	0.0740	0.0390	-0.0393	-0.0403	0.00316
nat_ht	0.257**	0.252*	0.237*	0.120	0.148	0.134
mathinf_ht	-0.0374	-0.0105	0.0154	-0.0285	0.0267	-0.0227
eng_ht	0.102	0.106	0.127	0.0935	0.0940	0.0468
econ_ht	0.253**	0.232**	0.235**	0.172**	0.193**	0.131
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	1,052	936	913	1,052	936	913
R-squared	0.061	0.130	0.168	0.031	0.104	0.160
Method	OLS	OLS	OLS	OLS	OLS	OLS

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

Table 9: Baseline regressions for university degree

nomics and natural science degree has a positive and statistically significant effect for high-tech entrepreneurs. In the second column all other personal characteristics are included. It contains sex, nationality, experience, the situation prior to the foundation of the start-up, motives for foundation and ownership of the start-up. Ownership 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[1]. As can be seen in all columns, the relation between economics degree and innovation is statistically significant and negative. In contrast, for economists in the high-tech industry the effect is statistically significant and becomes positive. The overall net effect is positive for the high-tech industry. This effect seems to be robust among all

[1]Additional regression results can be provided upon request. Contact see at front page.

specifications. Furthermore, we do not find a 'nerd effect'. Having a technical education does not lead to more innovation in the high-tech industry. This result shows that economists seem to weight r&d more or need more r&d compared to other fields. 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 again 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 economics degree in the high-tech industry leads to higher innovation. However, this is not true when firm characteristics are included as control variables. In this case, the economics variable in the high-tech industry becomes insignificant. For all other specifications this result is robust across the specifications. The results indicate that entrepreneurs with economic education in the high-tech industry are more able to release a product. The results for market release have to be interpreted with caution because of the last column. 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 10 illustrates. The commercial dummy is weakly significant in the first specification, while the social dummy is statistically significant. Furthermore, the social eduction in the high-tech industry becomes weakly significant in the second specification. All other education variables are insignificant. The education effect is even weaker when using *mrel* as dependent variable. Summarized, there is neither a 'nerd effect'for entrepreneurs with university degree nor with practical education. For entrepreneurs with a university degree an economics degree increases innovation, while there is no effect for practical education. 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 try to investigate whether the results mostly depend on the underlying definitions.

Variables	r&d	r&d	r&d	mrel	mrel	mrel
comm	-0.0532*	-0.0500	-0.0443	-0.0140	-0.00428	0.00421
tech	-0.0217	-0.0354	-0.0304	-0.0581	-0.0271	-0.0177
social	-0.0780**	-0.0670	-0.0642	-0.0268	0.0154	-0.000270
othserv	0.0160	0.0242	0.0183	-0.0191	-0.00162	-0.0302
ht	0.205***	0.227***	0.215**	0.116	0.160**	0.155**
comm_ht	0.0405	-0.00206	-0.0196	-0.0464	-0.0823	-0.0933
tech_ht	-0.0989	-0.117	-0.0982	-0.0404	-0.0891	-0.0741
social_ht	-0.131	-0.174*	-0.148	-0.0811	-0.155	-0.117
othserv_ht	0.0661	0.112	0.125	0.155	0.115	0.160
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	2,503	2,188	2,107	2,503	2,188	2,107
R-squared	0.036	0.060	0.098	0.014	0.055	0.102
Method	OLS	OLS	OLS	OLS	OLS	OLS

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

Table 10: Baseline regressions for practical education

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. The results are not reported but the significance and signs do not change.

That is why in the following OLS is again used. As argued before, further measures are employed to check further robustness of the results. 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* is a self-reported measure that provides information about the innovation level on an ordinal scale. The main focus of this variable represents the regional scope of the innovation. An ordered probit approach is used for evaluation. Table 11 reports the results for a university degree.

Variables	exp	exp	exp	new	new	new
nat	1,653	2,027	1,648	0.392*	0.387	0.304
mathinf	3,362	951.6	-539.4	0.128	0.0285	0.133
eng	-611.7	-528.4	-609.8	-0.0551	-0.0435	0.0383
econ	84.76	573.6	228.6	-0.162	-0.188	-0.128
ht	1,707	8,040	5,755	-0.122	-0.187	-0.106
nat_ht	11,576	4,714	4,596	0.470	0.574	0.567
mathinf_ht	1,988	-1,141	1,842	-0.122	0.0661	-0.118
eng_ht	3,391	-3,979	-2,928	0.328	0.367	0.235
econ_ht	7,396	-1,755	1,122	0.522*	0.629*	0.476
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	623	554	546	1,052	936	913
R-squared	0.066	0.115	0.173			
Method	OLS	OLS	OLS	OProbit	OProbit	OProbit

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

Table 11: OLS and ordered probit regressions for university degree

All specifications are characterized by insignificant education variables. Therefore, education seems not to play an important role. Comparing *new* with *mrel* leads to similar results because both variables have a high correlation due to its construction. Nevertheless, the effect of economic education for entrepreneurs with university degree is weaker from a statistical point of view. Table 12 shows the results for practical education.

For R&D expenditures per employee another picture emerges. Having a social or other services apprenticeship is negatively correlated with innovation. Compared to the baseline regressions the importance of education switches among the amount of education. The results for the regional scope of the innovation show that all results become insignificant. *pat_ use* includes a time dimension showing whether patents today or in future play a role for the start-up. The results 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 analyze entrepreneurs but rather patenting behaviour by all companies. Table 13 shows the regression results for university degree,

Variables	exp	exp	exp	new	new	new
comm	-107.4	-252.7	-308.6	-0.00462	0.0187	0.115
tech	155.4	465.4	372.5	-0.207	-0.111	-0.0245
social	-260.1	-363.3	-524.9	-0.111	0.0440	0.0571
othserv	-188.4	-429.6	-560.6	-0.0897	-0.0531	-0.152
ht	4,456**	5,130**	5,099**	0.405	0.584**	0.650**
comm_ht	2,073	1,467	1,329	-0.141	-0.294	-0.460
tech_ht	-2,631	-3,268	-3,247	-0.0589	-0.271	-0.297
social_ht	-3,327*	-3,993*	-3,916*	-0.270	-0.562	-0.520
othserv_ht	-3,859**	-3,392**	-3,673**	0.426	0.351	0.524
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	1,436	1,241	1,210	2,503	2,188	2,107
R-squared	0.046	0.066	0.081			
Method	OLS	OLS	OLS	OProbit	OProbit	OProbit

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

Table 12: OLS and ordered probit regressions for practical education

14 for practical education. Again OLS is used as for the baseline regressions.

All educational variables are insignificant for university degree and practical education as the tables show. It could be that individuals with a technical background are more innovative than other persons. However, this development is not fostered by entrepreneurs with technical 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 15 shows the comparison of product and process innovation for entrepreneurs with university degree.

Economists seem to focus more on product innovation because in two columns there is a positive effect in the high-tech industry. However, this effect vanishes when controlling for firm characteristics. The results are to some extent comparable to the baselines regressions using *mrel* where the type of innovation is not differentiated. For process innovation all education

Variables	pat_use	pat_use	pat_use
nat	0.0578	0.0584	0.0418
mathinf	-0.0372**	-0.0250	-0.0426
eng	0.0155	0.0110	0.00908
econ	0.0165	0.0148	0.0140
ht	0.00261	0.0141	0.00670
nat_ht	0.180**	0.180*	0.165*
mathinf_ht	0.0816	0.0734	0.0856
eng_ht	0.0598	0.0348	0.0406
econ_ht	0.0579	0.0321	0.0277
Time Effects	Yes	Yes	Yes
Entr. Char.	No	Yes	Yes
Firm Char.	No	No	Yes
Observations	1,052	936	913
R-squared	0.039	0.083	0.106
Method	OLS	OLS	OLS

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

Table 13: OLS regressions for university degree

Variables	pat_use	pat_use	pat_use
comm	0.00180	0.00408	0.00319
tech	0.00110	0.00600	0.00616
social	-0.0179	-0.00907	-0.0109
othserv	-0.000849	-0.00807	-0.0164
ht	0.0758*	0.0907**	0.0849**
comm_ht	-0.0250	-0.0391	-0.0352
tech_ht	-0.0464	-0.0612	-0.0529
social_ht	-0.0376	-0.0512	-0.0417
othserv_ht	-0.0294	-0.0175	-0.00531
Time Effects	Yes	Yes	Yes
Entr. Char.	No	Yes	Yes
Firm Char.	No	No	Yes
Observations	2,503	2,188	2,107
R-squared	0.008	0.030	0.045
Method	OLS	OLS	OLS

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

Table 14: OLS regressions for practical education

Variables	prod	prod	prod	proc	proc	proc
nat	-0.100	-0.0763	-0.111	0.0297	0.0189	0.0694
mathinf	0.115	0.193	0.218	0.124	0.148	0.170
eng	-0.0360	0.0381	0.0453	0.00199	0.0264	0.0318
econ	-0.109	-0.0620	-0.0720	0.0556	0.0678	0.0574
ht	0.0330	0.127	0.158	0.0692	0.131	0.156
nat_ht	0.316**	0.254	0.254	0.0675	0.0454	-0.0890
mathinf_ht	-0.215	-0.278	-0.337*	-0.120	-0.137	-0.189
eng_ht	0.0335	-0.0876	-0.130	0.0793	0.00964	-0.0129
econ_ht	0.326**	0.261*	0.219	0.174	0.104	0.0469
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	732	650	636	739	655	641
R-squared	0.039	0.073	0.118	0.033	0.056	0.112
Method	OLS	OLS	OLS	OLS	OLS	OLS

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

Table 15: OLS regressions for university degree

variables become insignificant. Table 16 shows the regression results for practical education.

There is an overall negative net effect of having an apprenticeship of other services and being in the high-tech industry. Furthermore, technical and commercial education is negatively correlated with product innovation for high-tech start-ups. In contrast, there is a positive effect of having a social education and being in the high-tech industry for process innovation. All these 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 in 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.

Variables	prod	prod	prod	proc	proc	proc
comm	0.0690	0.0873	0.0945*	-0.0221	-0.0129	-0.0162
tech	-0.00883	0.00604	0.0260	-0.0486	-0.0611	-0.0651
social	-0.00739	-0.000646	-0.0101	-0.0537	-0.0296	-0.0597
othserv	0.175***	0.186***	0.158**	0.00879	-0.0103	-0.0220
ht	0.239**	0.303***	0.336***	-0.0657	-0.0799	-0.100
comm_ht	-0.143	-0.225*	-0.240**	0.149	0.126	0.116
tech_ht	-0.142	-0.215*	-0.238**	0.146	0.164*	0.188*
social_ht	-0.0835	-0.134	-0.128	0.266**	0.237**	0.274**
othserv_ht	-0.324*	-0.392**	-0.374**	-0.119	-0.0950	-0.0801
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	1,715	1,502	1,439	1,732	1,516	1,449
R-squared	0.020	0.041	0.072	0.018	0.038	0.057
Method	OLS	OLS	OLS	OLS	OLS	OLS

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

Table 16: OLS regressions for practical education

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’, whether for entrepreneurs with university degree or 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. The education variables are all insignificant but the firm characteristics matter. In general, the results do not imply that individuals with technical education have less worth than economists. 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. It is probably the case that these people self select into research and development units of small or 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. However, in future research it would be nice to look at this feature to provide better policy advice. Our findings should be interpreted with caution. They suggest that such patterns exist for the population of Germany but they do not necessarily have to be true in general. Robustness checks with other proxies for innovation are conducted to capture more dimensions of the whole innovation process. The definition of innovation highly influences the results. Nevertheless, the central conclusion that there is no 'nerd effect'is maintained.

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