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New ventures in Cleantech: opportunities, capabilities and innovation outcomes

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Abstract

Facing the challenge of climate change, innovations that imply environmental benefits create business opportunities for entrepreneurs. This paper analyzes innovation capabilities of startups in Cleantech and how the innovation outcomes of those startups develop over time. Based on the Mannheim Foundation Panel and applying propensity score matching, a cohort of 566 Cleantech startups is analyzed and compared with a control group of non-Cleantech startups. We find that startups in Cleantech have, on average, higher innovation capabilities compared with all startups. However, Cleantech startups are a heterogeneous group including ventures using common technology and those developing new technology. Our econometric evidence shows that, ceteris paribus, Cleantech startups are more likely to combine existing technology in a novel way. Finally, we find that Cleantech startups do, on average, develop more market novelties in later years compared to theirs peers.

Keywords: Innovative startups, green innovations, Cleantech, capabilities, policies
JEL classifications: M13, O13, O25, O31

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1. Introduction

To address the challenge of climate change and scarce natural resources, many countries have developed policies that aim at fostering the Cleantech sector. In addition, consumer demand for environmentally friendly technologies has been high, thereby creating opportunities for entrepreneurs to develop novel technologies that are cleaner and conserve more energy and resources. Globally, the lead markets for green products, processes and services is estimated to have a volume of several billion euro. (BMUB, 2014). This creates opportunities for startups with innovative products, processes or services in Cleantech to establish and to grow. However, not much is known regarding the innovation contents of those startups. Do they develop new products based on own R&D, or do they mainly apply existing technology? Do they succeed in creating market novelties, or do they mainly use existing common technology?

A unique and yet unexplored opportunity for a systematic analysis of these companies is provided by the Mannheim Foundation Panel which allows us to identify Cleantech startups and a comparison group of non-Cleantech startups with similar characteristics as a control group. The definition of Cleantech in our study is in accordance with a previous study by Eckhardt and Shane (2003) who point out that clean technology entrepreneurship covers the development and utilization of goods and services that put together innovative clean energy technology solutions. Past studies have highlighted that the development of clean energy technology startups is driven by external factors, such as technological and market opportunities (Malen and Marcus, 2017). However, the internal characteristics that influence innovation activities of Cleantech startups are as yet left unexplored. The objective of our paper is to fill this gap.

Previous research has also identified the pull and push factors for „green“ or eco-innovations (Horbach et al., 2012). Cost savings and customer demand are particularly crucial pull factors that drive eco-innovation, while important push factors include technological capabilities, e.g., innovation intensity, R&D and firms' specific characteristics. These previous studies argue that pull and push factors play crucial roles in influencing green innovation.

A key feature of our paper is that we analyze the innovation capabilities of Cleantech startups and we link these capabilities both to the likelihood of generating general Cleantech solutions and to the general innovation outcomes of those startups. Cleantech startups in general are a heterogenous group of firms offering products or services that reduce negative environmental externalities. The environmental benefits of Cleantech products or services include higher levels of recyclability and energy efficiency, a reduction in the use of and impact on natural resources, and lowered noise emission. The realization of entrepreneurial opportunities in Cleantech depends on the exploitation of this business model and strategy (Teece, 2010). Consequently, it is essential to understand whether and how startups will gain a competitive advantage, (i.e., from innovation activities), when the development of entrepreneurial opportunities is combined with the use of capabilities, and other resources (Jantunen et al., 2005). In order to explore these factors more deeply, our paper focuses on entrepreneurial opportunities, innovation capabilities and innovation outcome for Cleantech startups.

Our measures of startups' innovation capabilities include several dimensions of assets that startups can use when developing their business. First and foremost, we assume that the background of the founder matters. We expect that both knowledge, in terms of educational background, and experience are important. A study by Romijn and Albaladejo (2002) confirms the importance of a founder's background, specifically, when technological startups have founders with engineering or science backgrounds. Technological startups involve intricate innovation and technology that is determined by a founder's human capital (Almus and Nerlinger, 1999). We consider the question of whether startups in Cleantech are founded by entrepreneurs that have more or less experience than other non-Cleantech startups. We also investigate the founder's educational degree or specific skills, to determine whether a founder's science, engineering and business degrees are important characteristics for Cleantech firms to generate market novelties, and higher levels of innovativeness. Second, since previous studies emphasize that technological capabilities (e.g., R&D activity) promotes green innovation (Horbach, 2008), in this paper, Cleantech startups' technological capabilities are also investigated. We address the question of whether innovation outcomes of Cleantech startups are contingent on the continuation of R&D. Furthermore, we provide evidence regarding the importance of patents in Cleantech startups' innovation activities and outcomes.

Our contribution to the literature is as follows. First, to our knowledge this is the first study that incorporates Cleantech startups' opportunities, capabilities and innovation using a comprehensive and detailed firm level panel data set allowing for a comparison between Cleantech new ventures and other new entrants on the market. Second, after performing a control group selection with the help of propensity score matching, we find that Cleantech startups have a higher likelihood of focusing on innovation and technological leadership as their primary business strategy. Third, based on the multinomial logit estimation, we can show that Cleantech startups produce more novel technologies than non-Cleantech startups. The higher innovation content of Cleantech startups is driven by technological capabilities and specific characteristics of the founder. For all startups, both the founder's industry experience and educational background are positively correlated with creating novel technology. Founders with engineering degrees are an important asset for Cleantech startups, since most Cleantech founders have an engineering background. Interestingly, we find that Cleantech startups develop significantly more market novelties during the years 2012-2014. The overall conclusion of our empirical analysis is that Cleantech startups do perform better, on average, than non-Cleantech startups conditional on their innovation capabilities, e.g., continuous R&D activity and holding patents.

Finally, our research may inspire policy makers and startups to promote the evolution of environmental technology as a key transformation to a green economy. By knowing capabilities and innovation outcomes of Cleantech startups, policies may encourage startups to focus on certain assets and capabilities that enhance the innovation performance of Cleantech ventures.

The remainder of the paper is organized as follows. Section 2 offers a review of previous studies. Section 3 describes the data and empirical approach. Section 4 reports both the descriptive and econometric results. Section 5 concludes.

2. Literature Review

In recent years, there has been a growing policy interest in addressing the issue of climate change. Investments in clean technology are widely considered as a key factor in climate change mitigation (Eyraud et al., 2013).

Clean technology is a rather broad concept, but most literature at the macro-perspective defines „clean " technology as innovations that generate energy efficiency, climate smarter buildings, less polluting transportation and cleaner production technologies (Dechezleprêtre et al., 2014). At the micro-level, a firm can be considered as Cleantech if it helps to protect the environment by facilitating environmentally friendly solutions by delivering products, services, or processes that contributes to limited or zero nonrenewable resources and creates significantly less waste than conventional offerings (Pernick and Wilder, 2007).

The theoretical literature on innovations in Cleantech has gained a boost in recent years from a number of studies relying on the endogenous growth theory. For example, Acemoglu et al. (2012) introduce a two-sector model of directed technical change where the final good can be produced by either „dirty" or „clean" inputs. Profit maximizing entrepreneurs build on previous innovations and direct their research to improving the quality of machines in one or the other sector. Key assumptions in the model are path dependency and inertia in research and socioeconomics systems. When dirty technology dominates the market, it is difficult for entrepreneurs with new technology to compete because several development steps are required to be a viable option for the market. The last R&D dollar will, therefore, be more profitable if invested in dirty technology. The theory predicts that without governmental interventions in terms of taxes, R&D subsidies and regulations, the introduction of clean technologies will be substantially delayed. Empirically, these predictions have been confirmed by studies, for instance of the automotive industry (Aghion et al., 2016) and the solar industry (ref is missing).

Given their significance in the policy debate, there are surprisingly few empirical studies dealing with Cleantech startups using data allowing for systematic analyses across firms and over time (for a survey of this limited literature, see Bjørnåli and Ellingsen (2014)). In looking at factors that promote startups in new technology, existing research distinguishes between three categories: individual, firm-specific and external factors. The first relates to characteristics of the founder or team of founders. An ample empirical literature has shown that all factors are important for the viability of the new firms (Almus and Nerlinger, 1999, Acs and Audretsch, 2003, Gilbert et al., 2006, Almus and Nerlinger, 1999, Bertoni et al., 2011).

However, compared to other new technology ventures, there are factors that might be of particular importance for Cleantech startups. As mentioned above, governmental support and regulations that enable clean technology to be profitable are such factors (see for instance Tsoutsos and Stamboulis, 2005). Besides economic incentives, some authors have suggested that entrepreneurs motivated by ethical concerns may be more successfully in green innovations (York and Venkataraman, 2010). It has also been found that Cleantech is still a sector with limited profitability (Bjørnåli and Ellingsen, 2014) and more dependent on governmental incentives than other firms.

There is a growing number of studies focusing on environmentally friendly technologies that are based on the Community Innovation Survey (CIS) or related data (see, for example Veugelers, 2012, Van Leeuwen and Mohnen, 2017), but they concern themselves almost exclusively with established companies and not with startups. Therefore, it is difficult to draw more profound conclusions about the particular prerequisites of Cleantech startups from these studies.

In summary, the existing literature on Cleantech startups is limited in terms of systematic studies. A major obstacle is the lack of information from regularly recurring data collections that allow us to observe new ventures over time. By using the Mannheim Foundation Panel as the database for our study, we can provide new evidence on the capabilities and innovation outcomes of Cleantech startups in a longitudinal perspective.

3. Empirical Approach

Our choice to analyze Cleantech startups in Germany is motivated by the fact that green technology from Germany has been growing due to a high demand for Cleantech solutions developed in Germany and also due to governmental support. According to BMUB (2014), Germany accounts for 14% of the world market share of the green tech global market.

3.1. Data and Variables

The Mannheim Foundation Panel provides information regarding a founder's specific characteristics, the specific characteristics each venture, and technological capabilities. It contains yearly information about new ventures founded over the period 2005-2014. In 2012, the Foundation Panel dedicates a specific survey about eco-credentials or environmental benefits of a firm's products or services referring to year 2011. The 2012 survey questions are designed to determine if the products and services of German Cleantech firms' offer positive environmental externalities. The startups' positive environmental benefits include various Cleantech solutions, e.g., emission reduction, energy efficiency and recyclability. Accordingly, our Cleantech startups are those that offer clean technology solutions as formulated in the survey. Our sample consist of a group of 566 Cleantech startups and of 566 non-Cleantech ventures. However, we follow those startup cohorts in later years as well, therefore, the time frame of our analysis includes the years 2011-2014. We present a list of variables, and descriptions in Table 1.

3.2. Econometric Estimations

To the best of our knowledge this paper is the first study that uses propensity score matching (PSM) to analyse Cleantech startups by defining a comparison group of non-Cleantech startups with similar characteristics, in particular with regard to innovation capabilities. Cleantech startups are defined as a treated group that we then match with the non-Cleantech group. Specifically, we apply PSM to match and analyze a cohort of 566 Cleantech startups, and we match that sample with a group of 566 non-Cleantech startups. PSM allows us to make comparisons in terms of outcome variables between treated and control groups conditional on similar characteristics (Rosenbaum and Rubin, 1984, 1985, Rubin, 1997). Previous studies have proved the effectiveness of PSM to investigate different characteristics of startups, e.g., academic spin-offs and non-academic startups (Cantner and Goethner, 2011, Stephan, 2014).

The application of PSM methodology follows Gantumur and Stephan (2011) and Stephan (2014). Let C_{i} represent a dummy variable that indicates Cleantech for startup i, with $C_{\mathrm{i}} = 1$ for „Cleantech" startups and $C_{\mathrm{i}} = 0$ „for non-Cleantech" ones. Let X_{i} denote a set of observed covariates. Then the propensity of belonging to $C_i \in \{0, 1\}$ is expressed conditional on X_i

$$p(C_i|X_i) = Pr(C_i = 1|X_i) = E(C_i|X_i). \tag{1}$$

We are interested in the difference between the expected Cleantechs' innovative outcome and that of non-Cleantechs. We define the average outcome of Cleantechs as $E[I_{\mathrm{i}1}|X_{\mathrm{i}}, S_{\mathrm{i}} = 1]$ and we have the average outcome of non-Cleantech's innovative performance as $E[I_{\mathrm{i}0}|X_{\mathrm{i}}, S_{\mathrm{i}} = 0]$, where $I_{\mathrm{i}1}$ denotes a Cleantech's innovation outcome, and $I_{\mathrm{i}0}$ represents a non-Cleantech's innovation outcome. Furthermore, we use the cohort of matched non-Cleantechs in order to estimate the innovative outcome of non-Cleantech ventures. Thus, in order to obtain the effect being a Cleantech venture on innovation outcome, we take the difference between a Cleantech's innovation outcome and a non-Cleantech innovation outcome as follows

$$\tau^{e} = E[I_{i1}|p_i, S_i = 1] - E[I_{i0}|p_i, S_i = 0]. \tag{2}$$

After performing PSM, we estimate probit models and multinomial logit regressions using the panel data based on the treated group (Cleantech) and control group (non-Cleantech) over years 2011-2014. By using the aforementioned models on the matched sample, we aim to investigate the impact of capabilities, a founders' background and experience, and the firms' characteristics on innovation outcomes.

Probit estimation is used in Model (3) and (4). In Model (3), our proxy for innovation outcome is the dummy variable *dnovel* that represents having a market novelty in either the regional, national or world market.

$$P(dnovel) = f(Cleantech, year, inno\ capabilities, founder\ characteristics, startup\ characteristics). \tag{3}$$

In Equation (3), *inno capabilities* consists of the variables *continuous R&D* and *patent*. *Founder characteristics* is captured by *founder's education background*, *founder's industry experience*, *founder's previous enterprise experience*, *founder's disciplinary background*, e.g., *economics/business*, *natural sciences*, *engineering*. Additionally, *startup characteristics* is defined by *startup em-*

ployees, *foundation year* and *industry sector*.

In Model (4), we use *dinno* as a proxy for innovation outcome as the dependent variable. *dinno=1* denotes that the startup has innovative products or services. The specification is

$$P(dinno) = f(Cleantech, year, inno\ capabilities, founder\ characteristics, startup\ characteristics). \tag{4}$$

We also employ multinomial logit regression for Models (3) and (4), where we use *inno* and *novel* as categorical dependent variables indicating innovativeness and market novelties with different outcomes. Dependent variable *inno* describes different degrees of innovation, e.g., $inno = 1$ (applying common technology), $inno = 2$ (new combination of existing technology), $inno = 3$ (application of third party new technology) and $inno = 4$ (self-developed technology). Dependent variable *novel* consists of $novel = 1$ (no market novelty), $novel = 2$ (novelty in a regional market), $novel = 3$ (novelty in Germany), $novel = 4$ (novelty in the world market).

4. Empirical Results

4.1. Propensity score matching and balancing test results

The descriptive statistics in Table 2 focus on the comparisons of Cleantech startup characteristics between the matched and unmatched samples. For simplicity, we perform a 1:1 nearest neighbors propensity score matching (PSM). In Table 2, we can see that after matching the differences between our treated (Cleantech) and control (non-Cleantech) groups are reduced. The balancing assumptions are confirmed for our most crucial exogenous variables between samples.

Based on the unmatched samples in Table 2, the innovation capabilities variables of founder specific characteristics (e.g, *Industry experience*, and *Founder enterprise*) indicate that the founder of Cleantech startups tend to be more skillful due to the Cleantech founders' experiences in the industry and their experiences in having founded previous ventures. The Industry experience variable is measured using a scale of 1-5, where higher numbers reflect increasing experience. Without matching, the *Industry experience* of a Cleantech founders is higher with about 3.4 on average compared to 3.2 of non-Cleantech founders. Nevertheless, the balancing assumption holds after matching, and leaves both groups with mean values of about 3.4. This indicates that both Cleantech and non-Cleantech founders have between 7-14 years, on average, of industry experience. Before matching, the founders of Cleantech startups are, on average, more experienced than those of non-Cleantech ones, since 43% of Cleantech startups' founders have established previous ventures. However, the difference in means between Cleantech and non-Cleantech startups are not significant in the matched sample. After matching, we can confirm that the mean value of the variable, *Founder enterprise*, is lower than that of Cleantech startups at 40%, which means, on average, fewer founders of non-Cleantech's ventures have established previous enterprises.

Interestingly, another founder specific characteristic that may influence the success factor of establishing Cleantech startups is a founder's background in engineering. Twenty eight percent of Cleantech founders hold an engineering degree, while founders' with other degrees, e.g., economics/business, natural sciences and math/computer degrees make up a very small percentage of the Cleantech founders. Another variable in the education domain describes a founder's educational qualifications. A majority of Cleantech founders, 46%, hold a college/university degree. Before matching, the second and third common degree held by a Cleantech startup founder is vocational college and professional qualification at 29% and 22%, respectively. This is in contrast with non-Cleantech founders who are more likely to have a professional qualification degree than a vocational college degree. A small fraction of 3.5% of Cleantech founders do not have an educational degree.

In Table 2, our technological capabilities measures (e.g, R&D and Hold patent for Clean- tech startups and non-Cleantech startups) reveal that it is more likely for Cleantech startups to hold patents and to conduct continuous R&D. Based on the unmatched and matched samples, 10.6% of Cleantech startups hold patent. Meanwhile, the percentage average of non-Cleantech startups that hold a patent is 5.3% in matched samples, and the difference in averages of *Hold patent* of Cleantech and of non-Cleantech startups is significant. Balancing assumption holds after matching, nevertheless, the percentage average of *Hold patent* for non-Cleantech startups tend to be lower than that of Cleantech startups at 8.1%. Furthermore, around 27% of Cleantech startups perform continuous R&D, whereas only around 23% of non-Cleantech startups conduct continuous R&D. Based on the results presented in Table 2, we draw the conclusion that it is more likely for Cleantech startups to have higher technological capabilities compared to non-Cleantech startups.

Cleantech startups are prevalent across industry sectors. Table 2 reveals that 26.3% of Cleantech ventures belong to technology intensive industries. The second biggest industry sector for Cleantech startups is the construction sector that comprises 16%. The third and fourth common industry sectors by percentage average are wholesale/retail market and high-tech manufacturing sector, respectively. The remaining industry sectors, e.g., cutting-edge tech manufacturing, software, non-high tech manufacturing, skill intensive services, and others constitute less than 10% for each corresponding industry sector.

4.2. Results for Cleantech startups' entrepreneurial orientation

In order to address entrepreneurial opportunity, we investigate the entrepreneurial strategy of Cleantech startups by drawing comparisons with the control group's entrepreneurial strategy. This analysis is based on the matched samples of Cleantech and non-Cleantech ventures with the same characteristics in 2013. The results for entrepreneurial orientations of the matched sample are shown in Table 3 and Table 4.

Table 3 reports that 46.8% of Cleantech startups opt for a business strategy that focuses completely on marketing tried-and-true products or services. We can also see that, around 25% of Cleantech startups have a business strategy that emphasizes innovation, technological leadership and R&D. Despite the preference of a larger number of Cleantech startups to focus on Strategy A, this strategy seems to be favored by tech startups in general. A majority of non-Cleantech startups also adopt a marketing of tried-and-true products or services as a business orientation. Interestingly, Cleantech startups have a higher relative frequency of following a dedicated strategy in innovation, technological leadership and R&D (Strategy B). Around 25% of Cleantech startups adopt Strategy B, whereas, a lower percentage of non-Cleantech startups focus on Strategy B, only around 17%.

Based on information provided in Table 4, a majority of Cleantech and non-Cleantech ventures select Totally A as their strategy for product improvement. This implies that both groups show a strong preference for incremental product improvement. The second most important strategy for Cleantech startups is Totally B, which indicates a strong preference for radical product improvement. Twenty percent of Cleantech ventures select Totally B as their product improvement orientation. On the contrary, the second best product improvement strategy for non-Cleantech startups is Preferably A, which implies a medium preference for an incremental product improvement. Around 21.4% of non-Cleantech startups select Preferably A as their entrepreneurial strategy for product improvement.

Both Table 3 and Table 4 illustrate the business strategy of Cleantech startups. The results show that Cleantech startups tend to exploit certain business strategies, e.g, either they totally focus on marketing of tried-and-true products or services, or they completely focus on innovation and technological strategy. The product improvement strategy tends to either totally focus on incremental improvement or otherwise radical improvement. This hints at the heterogeneous strategies that Cleantech startups employ in order to realize the opportunities and to meet the growing consumer demands in Cleantech products. A study by Nemet (2009) specifically investigates the wind power industry, and emphasizes that rapid technical change does not respond well to demand-pull. Yet, non-incremental technical change, in general, is influenced by technological-push (Dosi, 1988, Nemet, 2009). Particularly, in the environmental technology sector the need for non-incremental technical change is present, as the impact of Cleantech sectors might be minor, and the world still needs to meet climate goals set by policymakers. Interestingly, based on our matched samples, Cleantech startups have a higher likelihood of concentrating on innovation and technological as their business strategy. Their likelihood to focus on a radical product improvement is also higher than that of non-Cleantech startups.

4.3. Results for the innovation related outcome variables

We devote this subsection to presenting the descriptive statistic of our outcome variables for both Cleantech and non-Cleantech startups in matched samples over the period 2011-2014. The two outcome variables we analyze in this subsection are introduction of market novelties and innovation degree of new products or services.

Based on the information provided in Table 5, a majority of new ventures in both Cleantech and non-Cleantech have no market novelties (around 88%). However, Table 5 also reveals that Cleantech startups are more likely to generate market novelties in all markets when compared to non-Cleantech ventures. The percentage of Cleantech firms that have market novelties in the world market, the German market and regional markets are 5.94%, 5.94% and 4.36%, respectively.

Table 6 reports descriptive statistics for innovation degree of product and services for the Cleantech cohort and the control group. Clearly, we observe that Cleantech startups possess products with heterogeneous innovation degrees. The results show that for 34.5% of Cleantech startups, the most common innovation type is an innovative combination of existing technology. Since 26% of Cleantech startups introduce new products or services that utilize self-developed new technology, this shows that the likelihood of Cleantech startups to apply self-developed new technology is higher than that of the non-Cleantech cohort. The percentage of non-Cleantech startups that also develop new technology themselves is, at most, 21.5%.

4.4. Regression Results

This subsection discusses the results of our four regression models. Table 7 reveals the results for our probit models. Our *novel* variable is the dependent variable for the probit regression in the first column and has a value of 1 if the startup has introduced market novelties and 0 otherwise. Variable *inno* in the second column is denoting the innovation degree of products or services and has a value of 1 if the products are not based on common technology, but 0 otherwise.

The two probit regression models reveal that *Continuous R&D* and *Hold patent* are important drivers for both innovation outcome variables. This implies that R&D and technological capabilities enhance the innovation outcomes of Cleantech firms. Our result are in line with earlier work by Horbach (2008), who suggests that eco-innovation is driven by improvement in technological capabilities. The Cleantech dummy in both probit regressions is significant, suggesting that Cleantech ventures have a higher likelihood of generating innovation outcome compared to non-Cleantech startups. Based on the first probit regression, the probability of having a market novelty increases by 11.7% when the new venture belongs to the Cleantech group. This is due to the fact that the coefficient for the *Cleantech* dummy is significant at the 10% level. Furthermore, the probability of Cleantech startups having products or services that incorporate technology beyond common technology is 36.2% higher than that of non-Cleantech ventures.

Table 9 displays multinomial logit regression with *inno* as a dependent variable, where *inno* is now defined as a categorical variable instead of a binary one. The lowest innovation degree, i.e. applying common technology, it defined as the base level for the multinomial logit model. The coefficient of the *Cleantech* variables is significant and positive for all categories. This implies, that Cleantech firms are heterogeneous and include ventures that apply innovative combinations of existing technology, application of third party new technology and self-developed new technology more often than non-Cleantech firms do. It also shows that Cleantech startups have a higher probability of applying novel technologies than non-Cleantech ventures. The coefficient of *Cleantech* is the highest for a regression where the category of innovative combination of existing technology is the dependent variable. This suggests that Cleantech startups have the highest likelihood of having products or services that apply the aforementioned type of technology. These results are consistent with our previous analysis in Section 4.3.

The results presented in Table 9 indicate that when *Continuous R&D* is used as a technological capability measure, it explains an increase in innovation outcome for Cleantech firms. *Continuous R&D* coefficient is particularly significant at the 1% level when new ventures apply innovative combination of existing technology or they apply self-developed new technology. Furthermore, new ventures in Cleantech that hold a patent have a higher chance of increasing their innovation outcome. The *Holding patent* coefficient is significant at the 5% and 1% level, when Cleantech startups have new products or services that use an innovative combination of existing technology and self-developed new technology, respectively. On the contrary, the application of third party new technology is not influenced by having a patent which is in line with our expectation.

The determinants for having products and services that incorporate self-developed of new technology are shown in Table 9. This innovation category is driven by Cleantech startups' technological capabilities, the founder's natural sciences background, and having employees in founding year. As discussed earlier, both *Continuous R&D* and *holding patent* as technological capabilities measures are considered crucial resources that influence higher innovation outcome for Cleantech startups. Another essential capability of Cleantech ventures that stimulate higher innovation outcome is the founder's natural sciences background. Natural science as the educational foundation of a founder is significant at the 10% level and positively related with having new products or services that employ self-developed new technology. According to Visintin and Pittino (2014), when startups have employees in the year of startup, this is classified as an endowment resource for startups. Table 9 reveals that the *Startup has employees* coefficient is significant and positively correlated with self-developed technology. Accordingly, having employees in the year of establishment is another crucial asset for Cleantech startups.

The last result worth noting concerns the multinomial regression estimations for the novel variable which indicates having launched market novelties. The market novelty is a categorical variable that comprises market novelties in the regional, national (German) and world markets, respectively. Based on the results from Table 9, the Cleantech dummy is significant and positively related with novelty in the regional market. A Cleantech startup's likelihood of generating novelty in the regional market is higher than that of non-Cleantech startups. Furthermore, the *Cleantech* dummy is not significant for novelties neither in the German nor in world markets, respectively. However, Cleantech startups introduced new products or services at the scale of the world market in 2012, 2013 and 2014 but not significantly more than non-Cleantech firms.

Table 9 shows that for all startups technological capabilities measures, e.g., *continuous R&D*, *having patent*, the founder's educational background in *economics or business* are significant and positively related to the introduction of novel products or services on the world market. Thus, having an economics or business education background is an important factor for all startups to introduce market novelties in world markets. Technological capabilities measures are also essential factors that trigger Cleantech firms to create new products in novel ways (see Section 4.1). Based on the results of Table 9, technological capabilities are important for startups in general to create market novelties at the world market scale.

5. Conclusions

The growing demand for products and services that help to address the challenges posed by climate change and the scarcity of resources creates business opportunities for startups. This study analyses the innovation capabilities, entrepreneurial opportunities and outcomes of startups in Cleantech using data drawn from the Mannheim Foundation Panel. The analysis is performed by defining a comparison group of non-Cleantech startups by applying propensity score matching that have similar characteristics. We analyze the innovation outcomes of those startups in later years with respect to market novelties and innovation degree of their products using regression models.

Our findings can be summarized as follows. First, the Foundation Panel shows that Cleantech startups can be found in most industry sectors, and are not limited to high or medium technology manufacturing. Second, though Cleantech startups are quite heterogeneous in this respect, they have on average higher innovation capabilities in comparison to all startups. The results from matching show that Cleantech startups are more likely to hold patents and to engage continuously in R&D. Third, conditional on their innovation capabilities and in comparison with their peers, the regression models show that Cleantech startups are more likely to introduce market novelties in later years. Looking in more detail at this result, we find that the market novelties developed by Cleantech startups are more likely to be a novelty for the regional market, which might imply that those novelties might already exist for other markets. The results from the multinomial logit model also show that Cleantech startups are more likely to combine existing technology in a novel way. Thus, one tentative conclusion from this result is that Cleantech startups more likely focus on incremental instead of radical innovation. For all startups, we find that founders who hold a degree in business or economics positively contribute to the likelihood that the startup will introduce a world market novelty. Thus, this confirms previous research that the experience and background of the founders is an important part of the startup's innovation capability.

The success of startups in Cleantech is not only a result of the growing demand for green products and services, it is a combination of innovation capabilities, access to funding and policy support. This study did not analyze the roles played by access to funding and public support in determining the success of new ventures in Cleantech. These important areas are left for future research.

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Appendix

Table 1
Definitions of variables used in this study

Variables	Descriptions
Dependent Variables	
Inno	a categorical variable which describes different degrees of innovation 1 represents new products and services that apply common technology 2 represents new products and services that incorporate application of third party new technology 3 represents new products and services that apply self-developed new technology
Novel	a categorical variable that represent having market novelties. 1 represents having no market novelty 2 represents market novelty in regional market 3 represents market novelty in German market 4 represents market novelty in world market
Cleantech	is a dummy variable for which 1 represents new ventures in Cleantech, 0 denotes new ventures in non-Cleantech
Startup characteristics	
Foundation year	foundation year of startup
Startup has employees	1 describes startup has at least one employee in founding year 0 no employees in founding year
Tech capabilities	
Continuous R&D	1 represents continuous R&D. 0 is no continuous R&D
Having Patent	1 enterprise has at least one valid patent 0 no valid patents
Founders' characteristics	
Education background	a categorical variable which represents highest education qualification of founders. 1 represents founders with no education. 2 represents founders with apprenticeship qualification. 3 represents founders with vocational college degree 4 represents founders with college/university degree.

Economics/business	1 represents founders who have economics/business degree from college/university and 0 otherwise
Natural sciences	1 represents founders who have natural sciences degree from college/university and 0 otherwise
Engineering	1 describes founders who have engineering degree from college/university and 0 otherwise
Math/computer sciences	1 describes founders who have mathematics or computer sciences degree from college/university and 0 otherwise
Founder industry experience	founders' industry experience in years. 1 represents founders with $\leq$ 3 years experience. 2 represents founders with 3 $<x\leq 7$ years of experience. 3 represents founders with $7<x\leq 14$ years of experience 4 represents founders with 14 $<x\leq 21$ years of experience, 5 represents founders with $21\leq x\leq 32$ years of experience and 6 represents founders with $>$32 years of experience.
Founding previous enterprise	1 describes when one of the founders has had an enterprise before and 0 otherwise
Founding team	1 describes team-foundation and 0 otherwise
Public support	1 startups receive public support and 0 ortherwise
Industry Sectors	Classification of industry based on WZ2008-code
Cutting-edge technology manufacturing	20.20, 21.10, 21,20, 24.46, 25.40, 26.11,26.20, 26.30, 26.40, 26.51, 26.60, 30.30,30.40, 32,50
High-technology manufacturing	20.13, 20.14, 20.16, 20.17, 20.41, 20.51, 20.53, 20.59, 22.11, 22.19, 23.19, 26.70, 27.11, 27.12, 27.20, 27.40, 27.90, 28.11– 15, 28.23, 28.24, 28.29, 28.30, 28.41,28.49, 28.92–96, 28.99, 29.10, 29.31, 29.32, 30.20
Technology-intensive services	61.1–3, 62 (without 62.01), 63.1, 71.1–2, 72.1
Software	62.01
Non-high-tech manufacturing	10–33 (without cutting-edge technology manufacturing and high-tech manufacturing)
Skill-intensive services	69.1–2, 70.2, 72.2, 73.1–2
Business oriented services	49.2, 49.5, 50.2, 50.4, 51.2, 52, 53, 61.9, 63.9, 64, 74.1, 74.3, 74.9, 77.1, 77.3–4, 78, 80–82
Consumer-oriented services	49.1, 49.3–4, 50.1, 50.3, 51.1, 55, 56, 58–60, 65–66, 68, 74.2, 77.2, 79, 85.5-6, 90–93, 95–96
Construction	41–43

Wholesale	45–47 (without 46.1)

Table 2
Difference of characteristics between green and non-green startups of unmatched and matched samples.

Variables		Cleantech =1 Mean	=0 Mean	%bias	%reduct bias	t-test tvalue	p>t
Founding team=1	U	0.314	0.312	0.5		0.1	0.92
	M	0.314	0.306	1.9	-274.5	0.32	0.75
Economics/business=1	U	0.099	0.177	-22.8		-4.29	0.00
	M	0.099	0.099	0.0	100.0	0	1.00
Natural sciences=1	U	0.060	0.058	1.0		0.2	0.84
	M	0.060	0.049	4.5	-342.7	0.78	0.43
Engineering=1	U	0.284	0.166	28.6		5.78	0.00
	M	0.284	0.253	7.7	73.1	1.21	0.23
Math/computer=1	U	0.025	0.068	-20.6		-3.75	0.00
	M	0.025	0.023	0.8	95.9	0.19	0.85
Industry experience	U	3.391	3.194	13.6		2.67	0.01
	M	3.391	3.334	3.9	71.2	0.66	0.51
Founder enterprise before	U	0.428	0.390	7.6		1.49	0.14
	M	0.428	0.403	5.0	33.9	0.84	0.40
Startup has employees=1	U	0.594	0.581	2.6		0.5	0.62
	M	0.594	0.562	6.5	-151.6	1.08	0.28
Public support=1	U	0.558	0.553	1.1		0.21	0.84
	M	0.558	0.542	3.2	-200.4	0.54	0.59
Hold Patent=1	U	0.106	0.053	19.9		4.11	0.00
	M	0.106	0.081	9.2	53.7	1.43	0.15
R&D=1	U	0.272	0.239	7.5		1.49	0.14
	M	0.272	0.231	9.3	-23.5	1.58	0.12
Educational background[a]							
No degree	U	0.035	0.034	0.8		0.15	0.09

	M	0.035	0.032	1.9	-150.9	0.33	0.742
Professional qualification	U	0.217	0.271	-12.6		-2.43	0.02
	M	0.217	0.256	-9.1	28.2	-1.54	0.12
Vocational college	U	0.290	0.220	16.1		3.21	0.00
	M	0.290	0.292	-0.4	97.5	-0.07	0.95
College/university	U	0.458	0.475	-3.5		-0.68	0.50
	M	0.458	0.420	7.4	-113.5	1.26	0.21
Industry sector[b]							
Cutting edge tech manufacturing	U	0.048	0.109	-22.8		-4.20	0.00
	M	0.048	0.046	0.7	97.1	0.14	0.888
High-tech manufacturing	U	0.102	0.039	24.9		5.28	0.00
	M	0.102	0.080	9.0	63.8	1.34	0.18
Technology intensive	U	0.263	0.180	20.2		4.04	0.00
	M	0.263	0.300	-9.0	55.5	-1.39	0.17
Software	U	0.049	0.126	-27.1		-4.97	0.00
	M	0.049	0.044	1.9	93.0	0.42	0.67
Non-high tech manufacturing	U	0.090	0.096	-2.0		-0.38	0.70
	M	0.090	0.131	-14.0	-608.2	-2.18	0.03
Skill-intensive services	U	0.035	0.084	-20.6		-3.79	0.00
	M	0.035	0.035	0.0	100.0	0	1.00
Business-oriented services	U	0.074	0.040	14.8		3.06	0.00
	M	0.074	0.078	-1.5	89.7	-0.22	0.82
Consumer-oriented services	U	0.060	0.155	-31.0		-5.69	0.00
	M	0.060	0.053	2.3	92.6	0.51	0.61
Construction	U	0.161	0.043	39.6		8.58	0.00
	M	0.161	0.090	23.8	39.9	3.61	0.00
Wholesale/retail market	U	0.117	0.129	-3.8		-0.73	0.47
	M	0.117	0.143	-8.1	-115.2	-1.33	0.19

U=unmatched, M=matched sample, [(a)] reference category: No degree. [(b)] reference category: cutting-edge technology.

Table 3
Entrepreneurial orientation for Cleantech and non-Cleantech startups for matched cohorts in 2013.
Strategy A represents marketing of tried-and-true products or services. Strategy B represents innovation, technological leadership, and R&D.

		Cleantech		
Entrepreneurial Orientation		=0	=1	Total
totally A	obs	112	108	220
	%	52.58	46.75	49.55
preferably A	obs	27	23	50
	%	12.68	9.96	11.26
undecided	obs	25	28	53
	%	11.74	12.12	11.94
preferably B	obs	13	14	27
	%	6.10	6.06	6.08
totally B	obs	36	58	94
	%	16.90	25.11	21.17
Total obs		213	231	444
		100	100	100
Pearson chi2(4)=		5.027	Pr=	0.285

Notes: *Cleantech*=0 denotes the non-Cleantech and *Cleantech*=1 indicates the Cleantech startups. The second row reports the relative frequency of each type of entrepreneurial orientation for each group.

Table 4
Entrepreneurial orientation for Cleantech and non-Cleantech startups for matched cohorts in 2013. Strategy A represents incremental product improvement. Strategy B represents radical product improvement.

Entrepreneurial Orientation: Incremental vs radical product improvement		Cleantech =0	Cleantech =1	Total
totally A	obs	109	125	234
	%	50.70	53.88	52.35
preferably A	obs	46	27	73
	%	21.40	11.64	16.33
undecidedly	obs	21	27	48
	%	9.77	11.64	10.74
preferably B	obs	9	7	16
	%	4.19	3.02	3.58
totally B	obs	30	46	76
	%	13.95	19.83	17.00
Total obs		215	232	447
		100	100	100
Pearson chi2(4) =		9.775	Pr=	0.044

Notes: *Cleantech*=0 denotes the non-Cleantech and *Cleantech*=1 indicates the Cleantech startups. The second row reports the relative frequency of each type of entrepreneurial orientation for each group.

Table 5
Descriptive statistics for having market novelties from Cleantech and non-Cleantech startups after matching over period 2011-2014

Variable *novel*		Cleantech =0	=1	Total
No market novelties	obs	1,301	1,268	2,569
	%	88.38	83.75	86.03
Regional market novelties	obs	40	66	106
	%	2.72	4.36	3.55
German market novelties	obs	59	90	149
	%	4.01	5.94	4.99
World market novelties	obs	72	90	162
	%	4.89	5.94	5.43
Total	obs	1,472	1,514	2,986
	%	100	100	100
Pearson chi2(3) =		14.66	Pr =	0.02

Notes: Market novelty (*novel*) represents introduction of new products into market. *Cleantech*=0 denotes the non-Cleantech and *Cleantech*=1 indicates the Cleantech startups. The second row reports the relative frequency of each type of market novelty for each group. *novel*=1 represents non-market novelty. *novel*=2 represents novelty in regional market. *novel*=3 denotes novelty in national market, *novel*=4 denotes novelty in the world market.

Table 6
Descriptive statistics of innovation degree for Cleantech and non-Cleantech startups after matching over period 2011-2014, selected sectors

Variable *inno*		Cleantech		
		=0	=1	Total
Common technology	obs	160	110	270
	%	36.95	23.26	29.8
New combination of existing technology	obs	115	163	278
	%	26.56	34.46	30.68
Application of third party new technology	obs	65	79	144
	%	15.01	16.7	15.89
Self-developed new technology	obs	93	121	214
	%	21.48	25.58	23.62
Total	obs	433	473	906
	%	100	100	100
Pearson chi2(3) =		20.8	Pr=	0.000

Note: Innovation degree (*inno*) represents new product/service innovation degree. *Cleantech*=0 denotes the non-Cleantech and *Cleantech*=1 indicates the Cleantech startups. The second row reports the relative frequency of the innovation degree for each group. *inno*=1 denotes testing common techniques, *inno*=2 denotes new combination of common techniques, *inno*=3 denotes third party's new techniques, *inno*=4 denotes self developed new techniques.

Table 7
Probit estimation results for market novelties and innovation degree of new product or service

	prob(dnovel=1)	prob(dinno=1)
Startup characteristics		
Cleantech=1	0.117*	0.362***
	(1.71)	(3.74)
Year=2012	0.163*	0.151
	(1.95)	(1.03)
Year=2013	0.179*	0.142
	(1.86)	(0.84)
Year=2014	0.101	0.0424
	(0.92)	(0.22)
Foundation year=2010	0.240*	0.176
	(1.66)	(0.95)
Foundation year=2011	0.396***	0.149
	(3.04)	(0.90)
Startup has employees =1	-0.0165	0.162
	(-0.22)	(1.59)
Inno capabilities		
Continuous R&D=1	0.940***	0.733***
	(11.78)	(6.45)
Hold patent=1	0.601***	0.483***
	(5.93)	(2.84)
Education background$^{(a)}$		
Founder apprenticeship	0.0955	-0.845**
	(0.40)	(-2.33)
Founder vocational college	-0.0955	-0.835**
	(-0.40)	(-2.33)
Founder college/university	0.324	-0.608
	(1.31)	(-1.60)
Economics/business =1	0.142	0.140
	(1.17)	(0.70)
Natural sciences =1	0.0922	0.145
	(0.67)	(0.69)
Engineering =1	-0.134	-0.239
	(-1.21)	(-1.41)
Math/computer science= =1	-0.0866	0.160
	(-0.45)	(0.59)
Other experience		

Industry experience	0.0262	0.0404
	(1.05)	(1.15)
Founder enterprise before=1	0.0453	0.0190
	(0.64)	(0.19)
Startup's industry sector$^{(b)}$		
High-tech manufacturing	-0.231	-0.477**
	(-1.40)	(-2.13)
Technology intensive	-0.284*	-0.429**
	(-1.92)	(-2.17)
Software	-0.236	0.115
	(-1.27)	(0.42)
Non-high tech manufacturing	-0.242	-0.735***
	(-1.41)	(-3.42)
Skill-intensive services	-0.255	0.113
	(-1.18)	(0.16)
Business oriented services	-0.0625	-0.783*
	(-0.33)	(-1.72)
Consumer-oriented services	0.148	-1.040*
	(0.67)	(-1.66)
Construction	-0.133	-0.915***
	(-0.77)	(-2.85)
Wholesale	-0.256	-1.409**
	(-1.36)	(-2.01)
Cons	-2.024***	0.794*
	(-6.77)	(1.89)
Obs	2586	906

Notes: t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Dummy variable *dnovel* indicates that the startup has introduced a market novelty.
Dummy variable *dinno* indicates that the startups has innovative (new) product(s) which is/are not based on common technology. Only selected sectors.

Table 8
Marginal effects for market novelties and innovation degree of new product or service, probit estimation Table 7

	prob(dnovel=1), dy/dx	prob(dinno=1),dy/dx
Startup characteristics		
Year=2012	0.0303*	0.0428
	(1.91)	(1.05)
Year=2013	0.0335*	0.0402
	(1.80)	(0.86)
Year=2014	0.0183	0.0123
	(0.89)	(0.22)
Foundation year=2010	0.0366*	0.0512
	(1.74)	(0.94)
Foundation year=2011	0.0654***	0.0435
	(3.58)	(0.89)
Cleantech=1	0.0218*	0.103***
	(1.72)	(3.82)
Continuous R&D	0.225***	0.215***
	(10.04)	(6.70)
Holding patent	0.113***	0.138***
	(6.03)	(2.87)
Founder apprenticeship	0.0163	-0.212***
	(0.42)	(-2.88)
Founder vocational college	-0.0148	-0.209***
	(-0.38)	(-2.91)
Founder college/university	0.0621	-0.142*
	(1.47)	(-1.93)
Founder industry experience	0.00491	0.0115
	(1.05)	(1.15)
Founder previous enterprise=1	0.00849	0.00542
	(0.64)	(0.19)
Startup has employees=1	-0.00310	0.0464
	(-0.22)	(1.59)
Economics/business	0.0265	0.0400
	(1.17)	(0.70)
Natural sciences=1	0.0173	0.0415
	(0.67)	(0.69)
Engineering	-0.0252	-0.0682
	(-1.21)	(-1.42)
Math/computer science=1	-0.0162	0.0458
	(-0.45)	(0.59)
High-tech manufacturing	-0.0465	-0.128**

	(-1.35)	(-2.23)
Technology intensive	-0.0558*	-0.114**
	(-1.76)	(-2.39)
Software	-0.0474	0.0253
	(-1.26)	(0.43)
Non-high tech manufacturing	-0.0485	-0.210***
	(-1.37)	(-3.69)
Skill intensive services	-0.0507	0.0247
	(-1.20)	(0.16)
Business oriented services	-0.0135	-0.226
	(-0.33)	(-1.56)
Consumer oriented services	0.0345	-0.313
	(0.67)	(-1.51)
Construction	-0.0278	-0.271***
	(-0.75)	(-2.72)
Wholesale	-0.0511	-0.437*
	(-1.34)	(-1.95)
N	2586	906

Notes: t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Dummy variable *dnovel* indicates that the startup has introduced a market novelty.
Dummy variable *dinno* indicates that the startups has innovative (new) product(s)
which is/are not based on common technology. Only selected sectors.

Table 9
Multinomial logit regression results for variable *inno*, cohorts Cleantech and non-Cleantech startups, outcomes years 2011-2014

Categorical variable *inno*	Base level: applying common technology		
	New combination of existing technology	Application of third party new technology	Self-developed new technology
Startup characteristics			
Cleantech=1	0.725***	0.639***	0.457**
	(3.81)	(2.89)	(2.07)
Year=2012	0.420	0.350	-0.127
	(1.47)	(1.09)	(-0.39)
Year=2013	0.744**	-15.54	0.313
	(2.40)	(-0.02)	(0.89)
Year=2014	0.314	0.216	-0.262
	(0.85)	(0.51)	(-0.61)
Foundation year=2010	0.562	0.137	0.0798
	(1.56)	(0.32)	(0.19)
Foundation year=2011	0.244	0.206	0.295
	(3.81)	(2.89)	(2.07)
Startup has employees=1	0.124	0.274	0.504**
	(0.62)	(1.19)	(2.11)
Inno capabilities			
Continuous R&D	1.058***	0.501*	2.114***
	(4.72)	(1.84)	(8.33)
Holding patent	0.810**	0.274	1.305***
	(2.36)	(0.62)	(3.75)
Education background[(a)]			
Founder apprenticeship	-0.631	-1.873**	-1.735**
	(-0.78)	(-2.57)	(-2.12)
Founder vocational college	-0.606	-1.702**	-1.834**
	(-0.75)	(-2.37)	(-2.26)
Founder college/university	-0.256	-1.277	-1.417*
	(-0.31)	(-1.63)	(-1.68)
Economics/business=1	0.298	-0.0976	0.163
	(0.79)	(-0.20)	(0.39)
Natural sciences=1	0.178	-0.194	0.789*
	(0.42)	(-0.36)	(1.80)
Engineering=1	-0.297	-1.017**	-0.169
	(-0.91)	(-2.50)	(-0.47)

Math/computer science=1	0.416	-0.220	0.274
	(0.81)	(-0.32)	(0.47)
Other experience			
Founder industry experience	0.0204	0.111	0.133*
	(0.30)	(1.40)	(1.69)
Founder previous enterprise=1	-0.00370	-0.149	0.344
	(-0.02)	(-0.64)	(1.51)
Startup's industry sector$^{(b)}$			
High-tech manufacturing	-0.887**	-1.305**	-0.242
	(-1.98)	(-2.55)	(-0.50)
Technology intensive	-0.590	-0.938**	-0.646
	(-1.52)	(-2.22)	(-1.47)
Software	0.314	0.110	0.501
	(0.58)	(0.19)	(0.86)
Non-high tech manufacturing	-1.274***	-1.620***	-0.753
	(-2.97)	(-3.41)	(-1.55)
Skill intensive services	1.020	-17.24	-16.25
	(0.83)	(-0.00)	(-0.01)
Business oriented services	-1.285	-1.403	-15.52
	(-1.36)	(-1.46)	(-0.01)
Consumer oriented services	-17.22	-18.05	0.216
	(-0.01)	(-0.00)	(0.19)
Construction	-1.936**	-1.241**	-2.501**
	(-2.56)	(-1.99)	(-2.08)
Wholesale	-17.53	-1.737	-16.62
	(-0.01)	(-1.41)	(-0.00)
Cons	-0.217	1.125	-0.838
	(-0.23)	(1.27)	(-0.88)
Obs=906			

Notes: see previous Table. $^{(a)}$ ref cat: no degree, $^{(b)}$ ref cat: Cutting-edge technology manufacturing.

Table 10
Marginal effects of multinomial logit regression results for variable *inno* Table 9, cohorts Cleantech and non-Cleantech startups, outcomes years 2011-2014

	Categorical variable *inno*, marginal effect dy/dx			
	Applying common technology	New combination of existing technology	Application of third party new technology	Self-developed new technology
Cleantech=1	-0.106***	0.0797***	0.0329	-0.00634
	(-3.96)	(2.68)	(1.42)	(-0.25)
2012.jahr	-0.0461	0.0734*	0.0297	-0.0570*
	(-1.10)	(1.68)	(0.78)	(-1.75)
2013.jahr	-0.0306	0.189***	-0.170***	0.0115
	(-0.65)	(3.61)	(-11.37)	(0.28)
2014.jahr	-0.0262	0.0687	0.0207	-0.0631
	(-0.47)	(1.19)	(0.41)	(-1.48)
2010.gr_jahr	-0.0567	0.101*	-0.0108	-0.0332
	(-1.04)	(1.77)	(-0.24)	(-0.70)
2011.gr_jahr	-0.0422	0.0165	0.00686	0.0189
	(-0.86)	(0.33)	(0.17)	(0.43)
Continuously R&D=1	-0.211***	0.0323	-0.0553**	0.234***
	(-6.49)	(0.91)	(-2.02)	(7.37)
Having patent=1	-0.129**	0.0491	-0.0371	0.117***
	(-2.42)	(1.09)	(-0.85)	(3.75)
Founder apprenticeship	0.204***	0.102	-0.156*	-0.151
	(2.62)	(1.12)	(-1.91)	(-1.48)
Founder vocational college	0.198**	0.108	-0.136*	-0.170*
	(2.57)	(1.20)	(-1.68)	(-1.69)
Founder college/university	0.131*	0.127	-0.111	-0.148
	(1.65)	(1.40)	(-1.21)	(-1.43)
Economics/business=1	-0.0247	0.0506	-0.0292	0.00329
	(-0.42)	(0.96)	(-0.59)	(0.08)
Natural sciences=1	-0.0360	-0.0153	-0.0520	0.103**
	(-0.54)	(-0.27)	(-0.96)	(2.51)
Engineering=1	0.0805	-0.000533	-0.105**	0.0249
	(1.63)	(-0.01)	(-2.52)	(0.65)
Math/computer science=1	-0.0321	0.0708	-0.0521	0.0134
	(-0.39)	(0.99)	(-0.75)	(0.22)
Founder industry experience=1	-0.0125	-0.0109	0.00902	0.0144
	(-1.25)	(-1.02)	(1.07)	(1.59)
Founder previous enterprise=1	-0.00622	-0.0199	-0.0268	0.0529**
	(-0.21)	(-0.63)	(-1.09)	(1.99)

Startup has employees=1	-0.0437	-0.0254	0.0143	0.0548*
	(-1.52)	(-0.78)	(0.58)	(1.91)
High-tech manufacturing	0.135**	-0.0929	-0.120**	0.0787
	(2.24)	(-1.41)	(-2.11)	(1.47)
Technology intensive	0.112**	-0.0169	-0.0796	-0.0153
	(2.29)	(-0.28)	(-1.51)	(-0.33)
Software	-0.0345	0.0160	-0.0261	0.0446
	(-0.56)	(0.21)	(-0.39)	(0.76)
Non-high tech manufacturings	0.211***	-0.117*	-0.128**	0.0340
	(3.68)	(-1.78)	(-2.34)	(0.60)
Skill-intensive services	-0.0181	0.483***	-0.244***	-0.221***
	(-0.12)	(3.16)	(-5.03)	(-5.23)
Business oriented services	0.291*	-0.00646	-0.0636	-0.221***
	(1.81)	(-0.04)	(-0.50)	(-5.23)
Consumer oriented services	0.266	-0.356***	-0.244***	0.334*
	(1.46)	(-6.58)	(-5.03)	(1.84)
Construction	0.317***	-0.158	-0.0239	-0.135
	(2.97)	(-1.47)	(-0.27)	(-1.55)
Wholesale	0.595***	-0.356***	-0.0190	-0.221***
	(3.21)	(-6.58)	(-0.10)	(-5.23)
Obs	906	906	906	906

Notes: see previous Table. $^{(a)}$ ref cat: no degree, $^{(b)}$ ref cat: Cutting-edge technology manufacturing.

Table 11
Multinomial logit regression regression results for variable *novel*, cohorts Cleantech and non-Cleantech startups, outcomes years 2011-2014

Categorical variable *novel*	Base level: no market novelty		
	Novelty regional market	Novelty national market	Novelty world market
Startup characteristics			
Cleantech=1	0.472**	0.0940	0.0587
	(2.13)	(0.48)	(0.29)
year=2012	-0.198	0.277	0.976***
	(-0.75)	(1.12)	(3.97)
year=2013	-0.234	0.595**	0.681**
	(-0.73)	(2.33)	(2.40)
year=2014	-0.764*	0.433	0.839***
	(-1.70)	(1.44)	(2.69)
Foundation year=2010	0.870	0.290	0.445
	(1.33)	(0.76)	(1.08)

Foundation year=2011	1.350**	0.427	0.806**
	(2.23)	(1.24)	(2.17)
Startup has employees=1	-0.0318	-0.0143	-0.0963
	(-0.14)	(-0.07)	(-0.42)
Inno capabilities			
Continuously R&D=1	1.050***	1.599***	2.601***
	(4.03)	(7.05)	(9.72)
Having patent=1	-0.160	1.211***	1.261***
	(-0.35)	(5.08)	(5.37)
Education background			
Founder apprenticeship	0.691	-0.462	-0.119
	(0.91)	(-0.68)	(-0.14)
Founder vocational college	0.169	-0.715	-0.182
	(0.22)	(-1.06)	(-0.23)
Founder college/university	0.536	0.572	0.679
	(0.65)	(0.85)	(0.84)
Economics/business=1	-0.205	0.0314	0.589**
	(-0.42)	(0.10)	(2.04)
Natural sciences=1	0.0259	-0.188	0.501
	(0.05)	(-0.51)	(1.59)
Engineering=1	-0.689	-0.102	-0.169
	(-1.59)	(-0.35)	(-0.60)
Math/computer science=1	-0.566	-0.491	-0.0438
	(-0.70)	(-0.92)	(-0.10)
Other experience			
Founder industry experience=1	0.0231	0.0788	0.0583
	(0.29)	(1.10)	(0.81)
Founder previous enterprise=1	-0.164	0.455**	-0.174
	(-0.71)	(2.21)	(-0.83)
Startup's industry sector			
High-tech manufacturing	-1.239**	-0.252	-0.0415
	(-2.16)	(-0.58)	(-0.10)
Technology intensive	-0.738*	-0.311	-0.526
	(-1.69)	(-0.77)	(-1.29)
Software	-0.899	-0.402	-0.179
	(-1.48)	(-0.80)	(-0.38)
Non-high tech manufacturing	-0.740	-0.539	0.106
	(-1.44)	(-1.07)	(0.23)
Skill-intensive services	-0.239	-0.262	-1.052
	(-0.39)	(-0.46)	(-1.50)

Business oriented services	-2.038**	0.601	0.880
	(-2.47)	(1.14)	(1.61)
Consumer oriented services	0.336	-1.018	-0.896
	(0.63)	(-0.92)	(-0.80)
Construction	-0.741	0.300	-0.726
	(-1.48)	(0.61)	(-1.12)
Wholesale	-1.281**	0.0364	-0.117
	(-2.17)	(0.07)	(-0.21)
Cons	-4.240***	-4.716***	-5.834***
	(-4.10)	(-5.74)	(-6.13)
Obs	2,573		

Notes: See previous Table.

Table 12
Marginal effects of multinomial logit regression results for variable *novel* Table 12, outcomes years 2011-2014

	Categorical variable *novel*, marginal effect dy/dx			
	No market novelty	Novelty regional market	Novelty national market	Novelty world market
Cleantech=1	-0.0197	0.0158**	0.00299	0.000922
	(-1.53)	(2.07)	(0.34)	(0.11)
Year=2012	-0.0361**	-0.00980	0.00537	0.0406***
	(-2.29)	(-1.07)	(0.53)	(3.74)
Year=2013	-0.0359**	-0.0109	0.0243*	0.0224**
	(-1.96)	(-1.01)	(1.90)	(1.97)
Year=2014	-0.0235	-0.0240**	0.0148	0.0327**
	(-1.17)	(-2.35)	(1.05)	(2.31)
Foundation year=2010	-0.0367*	0.0153	0.00864	0.0128
	(-1.78)	(1.50)	(0.58)	(0.98)
Foundation year=2011	-0.0676***	0.0298***	0.0114	0.0264**
	(-3.74)	(3.50)	(0.87)	(2.26)
Continuously R&D=1	-0.226***	0.0354***	0.0692***	0.121***
	(-9.92)	(2.69)	(4.93)	(7.39)
Having patent=1	-0.0819***	-0.0101	0.0460***	0.0460***
	(-4.12)	(-0.66)	(4.42)	(4.82)
Founder apprenticeship	-0.00335	0.0235	-0.0169	-0.00325
	(-0.08)	(1.20)	(-0.61)	(-0.12)
Founder vocational college	0.0212	0.00527	-0.0227	-0.00379
	(0.54)	(0.29)	(-0.84)	(-0.14)
Founder college/university	-0.0619	0.0134	0.0243	0.0242

	(-1.45)	(0.64)	(0.81)	(0.85)
Economics/business=1	-0.0149	-0.00823	-0.00251	0.0257**
	(-0.64)	(-0.50)	(-0.18)	(2.12)
Natural sciences=1	-0.0110	0.000235	-0.0122	0.0230*
	(-0.43)	(0.01)	(-0.76)	(1.74)
Engineering=1	0.0304	-0.0230	-0.00215	-0.00522
	(1.42)	(-1.55)	(-0.17)	(-0.44)
Math/computer science=1	0.0365	-0.0184	-0.0209	0.00280
	(0.96)	(-0.67)	(-0.88)	(0.15)
Founder industry experience=1	-0.00554	0.000532	0.00311	0.00190
	(-1.18)	(0.20)	(0.97)	(0.62)
Founder previous enterprise=1	-0.00562	-0.00606	0.0222**	-0.0105
	(-0.41)	(-0.77)	(2.39)	(-1.18)
Startup has employees=1	0.00476	-0.000868	0.000110	-0.00400
	(0.34)	(-0.11)	(0.01)	(-0.41)
High-tech manufacturing	0.0534	-0.0483*	-0.00864	0.00352
	(1.53)	(-1.85)	(-0.43)	(0.18)
Technology intensive	0.0591*	-0.0334	-0.00839	-0.0174
	(1.78)	(-1.31)	(-0.44)	(-0.97)
Software	0.0557	-0.0392	-0.0141	-0.00242
	(1.46)	(-1.39)	(-0.65)	(-0.11)
Non-high tech manufacturing s	0.0434	-0.0345	-0.0212	0.0123
	(1.17)	(-1.27)	(-1.01)	(0.55)
Skill-intensive services	0.0490	-0.0102	-0.00475	-0.0340
	(1.07)	(-0.29)	(-0.18)	(-1.54)
Business oriented services	-0.0175	-0.0617**	0.0282	0.0511
	(-0.39)	(-2.40)	(0.89)	(1.49)
Consumer oriented services	0.0286	0.0325	-0.0322	-0.0289
	(0.53)	(0.81)	(-1.06)	(-0.86)
Construction	0.0367	-0.0346	0.0259	-0.0280
	(0.92)	(-1.28)	(0.93)	(-1.23)
Wholesale	0.0460	-0.0494*	0.00599	-0.00257
	(1.11)	(-1.86)	(0.21)	(-0.10)
N	2573	2573	2573	2573

Notes: See previous Table.