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On the way from invention to innovation: the role of applicant and inventor team characteristics

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Abstract

This paper investigates the impact of applicant and inventor team composition on patent commercialization in form of product creation. It outlines the importance of applicant and inventor team characteristics, i.e. specifically, size and internationality, on the speed of market authorization of a patent-related product and on the product quality. The analysis is performed for the European pharmaceutical industry. The product data is taken from the European Medicines Agency website for the period 2010-2019. Manual patent-product concordance is established with the help of the Pat-INFORMED database from the World Intellectual Property Organization and the Health Canada database. The created dataset presents combined data on patent and product characteristics. Results from an accelerated failure time model show that larger applicant teams as well as the presence of international applicants and inventors decelerate the market authorization of patent-related products. Results of the probit analysis show that larger inventor teams lead to patents of higher quality.

Keywords
patent; commercialization; pharmaceutical industry; survival analysis; probit regression

JEL Classifications
O31; O34; L65

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1. Introduction

Innovation often requires the effort of many parties: manufacturing, marketing, logistics etc. All these processes are seldom executed by sole individuals, but rather by teams. This also relates to the inventors. Combination of knowledge bases of individual inventors, especially those coming from different technological fields, might create more advanced innovations (Bercovitz & Feldman 2011).

The discussion on the importance of the different forms of alliances and collaborations is vividly present in innovation research. Thus, Ahuja (2000) shows the importance of direct and indirect time of inventive performance of firms in the chemicals industry. Baum et al. (2000) identify a positive effect of different types of alliances on Canadian biotech start-ups. Also for biotech firms, Zidorn & Wagner (2013) stress the impact of different types of alliances on the innovation success. There is also evidence, that lone inventors produce inventions of lower quality, than inventor teams do (Singh & Fleming 2010).

Most of these articles, however, are focusing on the initial, pre-commercial stages of innovation development by using patents as innovation proxy (Bouncken et al. 2018). In this case the so-called "Valley of Death" - the gap between patents and their commercial application - is not considered (Dean et al. 2020). Therefore, later articles added the product dimension to the analysis. For example, examining new molecular entities (NME) approvals data, Cohen & Cancer (2016) investigated how explorative and exploitative patents lead to innovation. Their results show the effect of knowledge heterogeneity among inventors' networks on breakthrough innovations creation as well as on the converting invention into innovations. Further, Wagner & Wakeman (2016) investigate factors, which may impact the speed of patent commercialization, Svensson (2012) analyses how commercialization may impact patent renewal decisions, and Li & Rizzo (2020) explore the role of firm characteristics on patent purchases. Despite these interesting studies, most of the factors influencing the success of patent transition into a product are far from being understood. In particular, characteristics of applicant and inventor teams are often left aside or only used as a control variable for the analysis. Nevertheless, including inventors with different but complementary knowledge bases into the team might lead to a product of higher quality and speed up the innovation process. The role of firms that apply for the market authorization of a patent, throughout this paper referred to as applicants, usually includes the identification of the strategic direction of patenting and the definition of the commercialization activities.

Because of the influential roles of inventors and applicants, it might be beneficial to know more about the impact of the composition of these teams. This is what this paper is aiming for. Firstly, the impact of joint patents as well as applicant and inventor characteristics on the speed of patent commercialization in the form of new product introduction is explored. Secondly, it is examined whether joint patents have a higher probability of commercial success than their single-applicant and single-inventor counterparts. Here, the geographical composition of the team is considered as well.

The analysis is performed on the European pharmaceutical industry. The reasons for this industry choice are the availability of data as well as the broad usage of patents as a way to protect intellectual property in the field (Pajunen & Järvinen 2018). Furthermore, the number of joint patents in the field is one of the highest across industries (Kim & Song 2007) and can be assigned to products with high precision (as shown by e.g. Stiller et al. 2021). Additionally, the developments in this industry play an important role in conquering global health-related challenges. This is also reflected by Sustainable Development Goals (SDGs) from the United Nations, in particular *SDG3: good health and well-being*, which became highly topical in the face of the current pandemic.

The product data for the analysis is taken from the European Medicines Agency (EMA) website (https://www.ema.europa.eu/en/medicines) for the period from the beginning of 2010 to the end of 2019. Obtained products are then related to the patent data in order to create patent-product concordance. This is done via the Pat-INFORMED database from the World Intellectual Property Organization (WIPO) and the Drug Patent Register from Health Canada. The econometric analysis is performed with 1) the product quality variable and 2) the time between patent application and product authorization as dependent variables. The applicant/inventor team characteristics are the main independent variables. Results of the analysis indicate that inventors mostly impact the quality product and applicants impact the speed of commercialization.

Findings of this paper contribute to the research on indicators of innovation by including the product dimension and not focusing exclusively on patents. Apart from that, the paper shows the importance of such under-researched variables as the composition of applicant and inventor teams. Furthermore, the analysis has implications for managers by supplying evidence of the importance of partnerships as well as showing which characteristics of co-applicants and co-inventors may be of special importance for commercial success.

The remainder of the paper is structured as follows. Chapter two presents the overview of existing literature on the topic and derives hypotheses. Chapter three introduces the data collection procedure and method used in the analysis. The results are presented and interpreted in chapter four. Finally, chapter five discusses limitations and avenues for further research and concludes.

2. State of the art and hypotheses

2.1 Introducing patent to product link

A large number of papers uses patent data as a proxy of innovation (Gambardella et al. 2008). One major issue of using patent data in innovation studies, however, is that patents rather represent invention but not innovation, as not all innovations are patented (Levin et al. 1987) and not all patents later are commercialized and become a product (Dean et al. 2020). Thus, more recent papers go beyond the usage of patent data and introduce new indicators in the analysis. Particularly, alternative sources of data including primary or secondary survey data (e.g. Archibugi et al. 2013a; 2013b), bibliometric data (e.g. Mina et al. 2007), or R&D statistics (e.g. Noori et al. 2017) are used more and more.

Other papers have deepened the understanding of the patent indicator by adding the product dimension to the analysis (de Solà-Morales et al. 2018) and establishing a link between patent and product indicators (de Solà-Morales et al. 2018, Stiller et al. 2021). This is especially important in regard to the fact that invention and innovation are not interchangeable terms: whereas invention relates to the creation of ideas, which then might be captured in patents, innovation refers to the commercialization of these ideas and the implementation of the learning process to the end product (Cohen & Caner 2016).

To deepen the knowledge of the invention-innovation link, research papers investigate the role of alliances on the success of subsequent innovation by a firm. Their focus includes radical innovation (D'Agostino & Moreno 2018), knowledge bases and institutional positions of alliance partners (Zhang et al. 2010, Dutta & Hora 2017), or inventors' academic careers (Shane & Khurana 2003). Further research articles deal with the factors behind specific patent commercialization (Wagner & Wakeman 2016, Svensson 2012), renewal decisions (Svensson 2012), or general patent transactions (Huang et al. 2018, Li & Rizzo 2020). The results of the analyses generally show the positive impact of different types of alliances on radical innovation performance (D'Agostino & Moreno 2018) and on the commercialization of an invention (Dutta and Hora 2017, especially for downstream alliances). Furthermore, there is evidence of a positive effect on patent value (Wagner & Wakeman 2016, Svensson 2012) as well as R&D investments of a large scale on commercial success (Li & Rizzo 2020). A negative effect of related uncertainty within teams can be found on the speed of commercialization (Wagner & Wakeman 2016).

The above-mentioned papers mostly focus on the importance of different factors (firm size, university-technology interaction, profiling inventors etc.) for the purpose of investigating: 1) commercialization and success of an invention (Cohen & Caner 2016, Dutta & Hora 2017), or 2) speed of the invention's commercialization (Svensson 2012, Wagner & Wakeman 2016, Li & Rizzo 2020). The composition of inventor and applicant teams themselves were often not considered or used as a control variable in these papers (e.g., in Svensson 2012). However, there exists strong evidence of the lower quality of sole-inventor patents (Singh & Fleming 2010), and of diverse teams being more likely to achieve invention commercialization (Bercovitz & Feldman 2011). Thus, there still exist gaps with regard to understanding the transition process of invention to product, which this paper aims to address.

Most of the above-stated research articles focus on the biotechnology or pharmaceutical industry. Reason for that is data availability based on the comprehensive information provided by medicines agencies all over the world, as well as the active patenting in these fields (e.g. Aggarwal & Hsu 2014, Hohberger 2014, Ouellette 2010). This allows to establish a clear connection between the patent data and product dimension. This paper as well focuses on the innovation in the pharmaceutical industry, particularly on the drugs authorized by the EMA. Thus, it is extending the research on product-related innovation indicators (e.g. Cohen & Caner 2016, Stiller et al. 2021) by concentrating on the measures of product success.

2.2 Hypotheses

Although the evidence on the impact of inventor and applicant teams on the speed and further success of invention commercialization is so far limited, valuable insights can be obtained by looking at the impact of these indicators. The rationale behind the importance of these indicators lies in the complementarity of knowledge bases of patent co-inventors and co-applicants and their ability to use existing knowledge. This knowledge might relate to the technical side of the invention or the possibilities of bringing the respective product to the market. With respect to the latter, proponents of a resource-based view outline that firms can gain competitive advantage by using complementary assets of their partners (Dutta & Hora 2017). Thus, knowledge is one of the main reasons for cooperation (Cantner & Meder 2007). Concerning the technical knowledge necessary to invent and to create a product based on the invention, the importance of actor's absorptive capacity, i.e. the ability to perceive, assimilate, and use knowledge, is highlighted in several studies (Cohen & Levinthal 1990). In this case, firms may profit from networks or teams of actors (both internally and externally, nationally and internationally) with differently specialized knowledge bases, which coordinate and 'mobilize' in order to produce the next invention (Gay et al. 2008).

Empirical evidence of the impact of applicant and inventor team characteristics on the resulting patent is also presented in recent research articles. Thus, Huang et al. (2018) provide evidence that assignee and inventor count as well as inventor country count have positive impact on patent transaction duration, whereas assignee country count has a negative impact on patent transaction duration. The latter fact may be explained by the additional coordination costs that arise as more organizations are involved in the invention, which may hinder team-building (Bercovitz & Feldman 2011). Svensson (2012) does not find a significant impact of the number of inventors on the speed of commercialization. However, his study shows faster commercialization of patents when small or micro firms are involved in the application.

In summary, based on the existing evidence it is expected that larger and diverse inventor teams lead to shorter time between patent application and commercialization, whereas larger and international applicant teams lengthen this period. It is important to note for the analysis of such a study, that the researcher has to account for the difference in the time of market authorization for different products (Wagner & Wakeman 2016).

H1: Larger applicant team leads to longer time between patent application and commercialization

H2: Larger inventor team leads to shorter time between patent application and commercialization

H3: International applicant team leads to longer time between patent application and commercialization

H4: International inventor team leads to shorter time between patent application and commercialization

The evidence of the importance of partnerships for invention and innovation success is broader. Already Ahuja (2000) and Baum et al. (2000) investigated the importance of different types of alliances for the innovative performance of firms. Dutta & Hora (2017) demonstrate a positive impact of, in particular, downstream alliances on commercialization success, which can be explained by a developed market presence and knowledge about development, production, and distribution of innovations in question. Singh & Fleming (2010) outline higher quality of collaborative patents as a result of recombination and search mechanisms. Additionally, an increase in the probability of a breakthrough invention is reported for collaborative patents (Singh & Fleming 2010). Cohen & Caner (2016) also state the importance of knowledge heterogeneity for the transition of exploitative inventions into breakthrough products. Hu et al. (2021) extend this evidence by showing an inverted U-shape relationship between inventor team size and high-quality patents, whereas for low-quality innovation a negative relationship is found.

There is also evidence of a positive impact of the diverse knowledge backgrounds of alliance partners, both technologically and geographically. Thus, Gay et al. (2008) state that foreign inventors lead to larger teams and higher-value patents. Bercovitz & Feldman (2011) also argue that firms may gain from diversity of the parties involved, whereas Cohen & Caner (2016) outline the importance of knowledge recombination in case of collaborative patents. For patents created with foreign partners, there exists an indication of increased commercialization value (Beaudry & Schiffauerova 2011) and increased knowledge-innovation relationship (Zhang et al. 2010).

Summing this evidence up, it is expected, that, for the case of patent-product relation, larger and international teams of both applicants and inventors lead to higher quality or value of the product.

H5: Larger applicant team leads to products of higher value

H6: Larger inventor team leads to products of higher value

H7: International applicant team leads to products of higher value

H8: International inventor team leads to products of higher value

3. Data and methods

3.1. Data collection and analytical procedure

The analytical approach of this paper is based on the combination and concordance between different data sources. Therefore, the relevant patent dataset along with the product dataset needed to be identified. The focus of the paper lies on the pharmaceutical industry. To remain in one regulatory and legal area, the evaluated data is from Europe only. The time frame for the analysis is the period from 2010 to 2019. This time frame is based on the data availability and allows to follow the corresponding patents, to identify relevant variables, including applicant- and inventor-related characteristics, and to estimate all necessary patent- and product-related characteristics.

The following steps describe the data collection and preparation procedure as well as further analytical steps taken in this paper. The analytical procedure is visualised in the figure below.

1. Identification of product dataset. This step includes identification of the product dataset based on the EMA authorized drugs. The product dataset is identified before the corresponding patent dataset because of the data accessibility.

2. Identification of related patents. Here, the patents, related to the identified drugs of step 1, are collected. This is done via manual reviews of International Non-Proprietary Name (INN) on the Pat-INFORMED database from WIPO (accessed under https://www.wipo.int/patinformed/). In cases where there was no data available from the Pat-INFORMED database, manual checks of medical ingredients or brand names was done via the Drug Patent Register from Health Canada (accessed under https://pr-rdb.hc-sc.gc.ca/pr-rdb/index-eng.jsp). In latter case European patent application was considered.

3. Definition of variables. At this step variables of interest (dependent & independent) and control variables are defined. These include patent- and product-related variables, as well as applicant and inventor characteristics.

4. Econometric analysis. Finally, the hypotheses tests are performed. For the case of the hypotheses regarding the speed of commercialization, the Accelerated Failure Time (AFT) Model is estimated. And for the analysis of product success, a hypothesis probit model is applied.

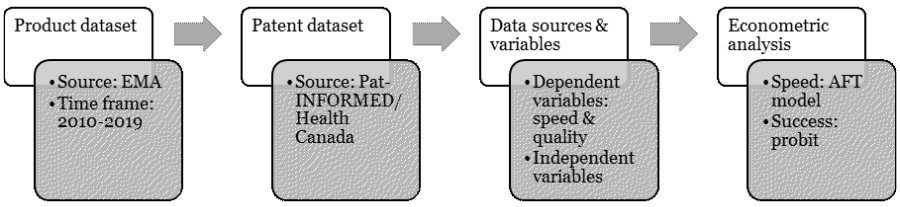


Figure 1: Analytical procedure

3.2. Product dataset

As mentioned above, the data collection procedure starts with the identification of the product dataset. This is comprised of the drugs, which were authorized by the EMA between 01.01.2010 and 31.12.2019. Authorization date means the 'Date of issue of marketing authorization valid throughout the European Union'. As a result, 796 drugs were identified. From this sample, 169 generic products were excluded as they were introduced after the related patents expired. The dataset consists of different product categories, including vaccines and veterinary drugs. The resulting dataset encompasses 627 drugs.

3.3. Patent dataset

In this step, the concordance between the identified product dataset and related patents is established. To do so, the Pat-INFORMED database from WIPO is used as a primary source. Pat-INFORMED contains information about drug-related patents, which is provided by twenty leading pharmaceutical companies themselves. It is possible to execute searches by entering the respective International Non-proprietary Names (INN), i.e. active pharmaceutical ingredients of the drug. As not all drugs are available in the Pat-INFORMED database, the data was supplemented by the entries from Patent Register from Health Canada by the government of Canada. This additional database is updated nightly and includes a large number of drugs, starting from March 12, 1993. Here, the search can be done based on medical ingredient or brand name.

Thus, drugs were manually checked for both databases in order to identify connected patents. 383 drugs did not have any patents connected to them according to both databases. Additionally, nine patents were excluded that were filed after the drug authorization or in the same year as drug authorization. Furthermore, four patents without identified inventors and applicants were omitted. Consequentially, 782 drug-patent entries from 514 patent families were identified as the patent dataset. These patents belong to 243 drugs. Lastly, as the time frame for this study is from 2010 to 2019, patents related to drugs authorized by the EMA before then were excluded from the sample. As the result, 467 patent families remained in the dataset belonging to 191 products.

3.4. Data sources & variables

Next, the considered patent dataset is extended by several variables for the econometric analysis. These variables can be categorized into dependent variables, independent variables, and control variables.

Dependent variables

Two dependent variables are used in this paper: one variable is related to the time from invention to innovation, and the second variable regards the success of the patent-related product. The time indicator is captured by the number of years between the priority application of a patent and the product's market authorization. A similar measure

was also used in other papers dealing with the timing of product introduction or patent purchase (e.g. Huang et al. 2018, Li & Rizzo 2020).

The success variable reflects the quality of the product. In case of patent data, the quality is often described by the number of citations, which a patent receives (e.g. Dahlin & Behrens 2005, Katila 2000, Shane 2001). For the product quality indicator, the number of new molecular entities (NME)[1], identified by the U.S. Food and Drug Administration (FDA), are often used (e.g. Dunlap et al. 2013, Cohen & Caner 2016). This indicator reflects the number of substances which were introduced to the US market for the first time by a given drug (Cohen & Caner 2016).

The NME indicator, however, mostly reflects the realities of US pharmaceutical industry. Apart from that, this measure does not directly reflect the quality of an introduced drug. For these reasons, Stiller et al. (2021) introduced a new measure, based on German health technology assessment (HTA). HTA in Germany is measured by the Federal Joint Committee (*Gemeinsamer Bundesausschuss*), which is the decision-making body of 'physicians, dentists, hospitals and health insurance funds' (Gemeinsamer Bundesausschuss 2018). Each drug appearing on the market is compared to an already existing one and a conclusion about the additional benefits of the new drug is issued by the Committee (Stiller et al. 2021). As the result of the benefit assessment, the following conclusions are possible[2]: major additional benefit, considerable additional benefit, minor additional benefit, non-quantifiable additional benefit, no additional benefit, and less additional benefit (Schulz et al. 2020). Non-quantifiable additional benefit in this case reflects the case, where existing data does not allow quantitative demonstration of the benefit. Less additional benefit shows, that the priorly existing drug/therapy has a higher benefit than the new one (Schulz et al. 2020).

As Stiller et al. (2021) in their paper dealt with a measurement for radical drugs, only major or considerable benefit were included as indicators in their analysis. This present study only examines the success of the innovation but not its extent. Thus, drugs receiving major, considerable, minor or non-quantifiable additional benefit assessment were considered qualitatively high and received a value of one according to this indicator. Those with none or lower benefit were not considered qualitatively high and received the value of zero. In order to be a qualitatively high drug it is required to show additional benefit in at least one field of application. Besides that, veterinary drugs were excluded from this indicator, as no information could be found regarding this category.

[1] According to FDA definition these are active moieties that have not been approved by FDA before (FDA 2020).
[2] From highest to lowest, based on comparison with an alternative treatment. Starting from 01.01.2011, each drug must receive a benefit assessment through HTA (Schulz et al. 2020).

Independent variables

Four independent variables, reflecting the research questions, were introduced. These include number of applicants, number of inventors, the presence of inventors from different countries, and the presence of applicants from different countries. All these indicators were manually extracted from patent documents. Number of applicants was calculated independent of the applicants' corporate structure. This means, for example, that if the head of a corporate group appeared on the patent application together with the subsidiary, the number of applicants is equal to two. The reason for this procedure is that coordination costs occur also inside the same corporate structure. For the case of inventor and applicant countries the variable takes the value of one if at least one inventor or applicant comes from a different country than other inventors or applicants.

Control variables

Furthermore, several control variables were included in the analysis. These relate to patent, drug, and actor characteristics and cover the following: 1) dummy of Anatomical Therapeutic Chemical (ATC) Classification of the drug on main group level. This variable reflects active substances in the drug and, thus, indicates the sphere of drug usage; 2) size of DOCDB simple patent family, given by the number of patents in the family. This indicator was taken from the PATSTAT database Spring 2019 (or 2019a) version and shows the number of patents behind a single invention and its connection to the same priority patent[3]. A larger patent family might implicate the strategic need of the company to search for patent protection in more countries and, thus, demonstrates the relevance of the underlying idea; 3) binary variable, which is equal to one, if the patent applicant is also market authorization holder, and zero otherwise. This information is taken from EMA along with patent documents; 4) binary variable, which is equal to one, if at least one applicant is relates to the category of small and medium-sized enterprises (SME), and zero otherwise. SME definition is based on the European Commission definition and consists of two conditions: a firm should have less than 250 employees as well as a turnover not exceeding 50 million Euro and/or an annual balance sheet total not exceeding 43 Million Euro (see Recommendation 2003/361/EC). This information was taken from Orbis firm database and extended by firm websites.

The overview of all variables with description and relevant sources of data is presented in the table below.

[3] Additional information can be found under https://www.epo.org/searching-for-patents/helpful-resources/first-time-here/patentfamilies/docdb.html

Table 1: Variables description

Level	Variable	Description	Data Source
Dependent variables	TIME	Period between (priority) patent application and drug authorization (in years)	EMA & Patent documents
	QUAL	Result of early benefit assessment (Stiller et al. 2021)	Gemeinsamer Bundesausschuss
Firm-level variables	NOINV	Number of inventors per patent	Patent documents
	NOAPPL	Number of applicants per patent	Patent documents
	CTRINV	Inventors belonging to the same (0) or different countries (1)	Patent documents
	CTRAPPL	Applicants belonging to the same (0) or different countries (1)	Patent documents
Control variables	ATC	Dummies of Anatomical Therapeutic Chemical (ATC) Classification on main group level[4]	EMA
	FAMSIZE	Size of DOCDB simple patent family	PATSTAT 2019a
	APPLAUTH	Whether patent applicant is also market authorization holder (1) or not (0)	EMA and patent documents
	SME	Whether at least one SME was among applicants (1) or not (0)	Orbis and firm websites

3.5. Econometric analysis

The econometric analysis of the paper consists of two parts, related to two research questions:

1) What impact does the composition of applicant and inventor teams have on the speed of patent commercialization? This question calls for the usage of survival analysis.

2) What impact does the composition of applicant and inventor teams have on the quality of commercialized patents? This question requires the usage of a regression model for a binary dependent variable.

The first research question, connected thematically to hypotheses 1-4, relates to the duration (in number of years) between the patent application and market

[4] Which includes the following main groups: A - Alimentary tract and metabolism; B - Blood and blood forming organs; C - Cardiovascular system; D – Dermatologicals; G - Genito-urinary system and sex hormones; H - Systemic hormonal preparations, excl. sex hormones and insulins; J - Antiinfectives for systemic use; L - Antineoplastic and immunomodulating agents; M - Musculo-skeletal system; N - Nervous system; P - Antiparasitic products, insecticides, and repellents; R - Respiratory system (for more information see https://www.who.int/tools/atc-ddd-toolkit/atc-classification). The distribution of patents according to ATC Classification groups is presented in the appendix.

authorization. Most papers use Cox proportional hazards model in order to deal with similar questions (e.g. Huang et al. 2018, Wagner & Wakeman 2016). This model, however, includes the assumption of a proportional hazard, meaning that the effect of a covariate can be seen as the multiplication of the hazard by some constant (Svensson 2012). However, this assumption was violated in the case of the present dataset. In this case, an accelerated failure time (AFT) model is often applied in articles (e.g. Cefis & Marsili 2005, Holmes et al. 2010, Shane & Khurana 2003). This type is an extension of linear models and assumes a specific parametric form for the effect of covariates and survival functions (Cefis & Marsili 2005). The most commonly used forms include exponential, log-logistic, log-normal, and Weibull. Based on the log-likelihood test, the Weibull model was chosen for the analysis here[5]. The Weibull AFT model can be expressed as follows (Liu & Lim 2018):

$$\log(t_i) = \boldsymbol{x'_i}\beta_i + \sigma\varepsilon_i \quad i = 1,2 \dots n \tag{1}$$

Where t_i denotes survival time, $\boldsymbol{x'_i}$ states for values of covariates, β_i represents regression coefficient, σ states for scale parameter.

The second research question, connected thematically to hypotheses 5-8, relates to the success of product underlying invention. Econometrically this question requires the usage of regression model for a binary dependent variable, as the success variable takes only values of one or zero. Previous research often used probit estimations for similar tasks (e.g. Bercovitz & Feldman 2011, Svensson 2012, Hu et al. 2021). This model is also suitable for the analysis of this paper. Mathematically it can be represented by following equation (Svensson 2012):

$$F^{-1}(P_i) = x_i\delta \tag{2}$$

Where P_i stands for the probability of a product having a positive early benefit assessment, F^{-1} represents the inverse of the cumulative normal distribution function, x_i sands the vector of independent and control variables, δ denotes parameters' vector.

4. Results

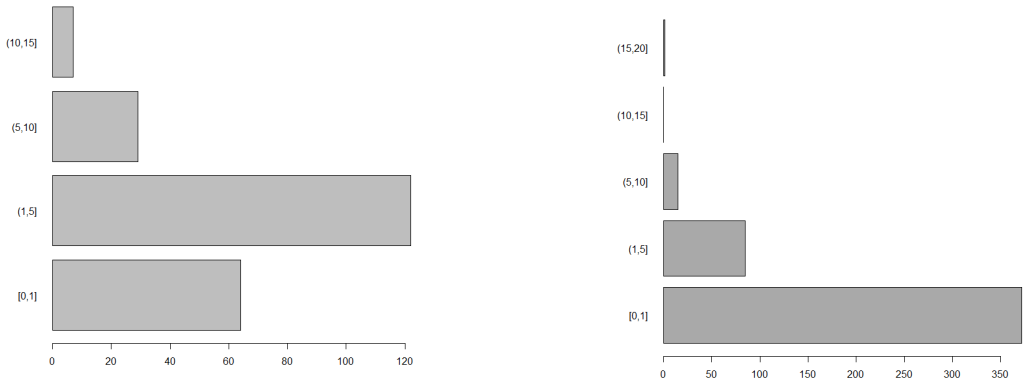
4.1. Descriptive statistics

The descriptive analysis begins with an exploration of patent and product data. Figure 2 below presents the statistics of the number of patents per one drug and the number of drugs for one patent. One patent may be related to more than one drug if two drugs have partially same International Nonproprietary Names (INN), reflecting a drug's active pharmaceutical ingredients. Regarding the number of patents per one product, most of

[5] The AFT model can be applied to censored and uncensored data. As in this dataset no censored values are present (all patents in question are commercialized), the robustness check is performed with the linear regression model. Log-likelihoods are presented in the appendix.

the products have between two and five patents connected to them. This corresponds with an evidence of Ouellette (2010), who noted on average 3,5 to 5 patents per drug (depending on drug type) in 2005 according to FDA with an increasing tendency over time. The highest number of patents per drug in the present dataset is 14 for the following five drugs: Elebrato Ellipta, Relvar Ellipta, Revinty Ellipta, Temyric Ellipta, Trelegy Ellipta. All these drugs relate do lung diseases, especially asthma. Such tendencies may show the importance of these drugs for a company (Ouellette 2010).

Figure 2 further shows, that most of the patents correspond to only one drug with a maximum of 18 drugs per patent. The most widely applied patent relates to the quite broad topic of 'Method of making particles for use in a pharmaceutical composition' and was applied for by Vectura Ltd. Because of the broad coverage the patent could affect such a large number of drugs.



Patents per one product *Products per one patent*

Figure 2: Patent and product statistics

Source: own calculation

Next, the number of patents and drugs per year is analysed over time (see Figure 3). Caused by the research design, the product dataset is available only for the period of 2010-2019. Here, a general downward trend can be observed in the last years, meaning less drugs were authorized by the EMA, starting from 2015-2016. Most of the drug-related patents were applied for between mid-2000s – beginning of 2010s.

Table 2 develops this evidence by presenting descriptive statistics on the dependent variables *TIME* and *QUAL.* It can be seen that the average time from the priority patent application to the market authorization of the related drug is around nine years. It should be noted, that here only the earliest drug-related authorization is considered, i.e. if the patent is related to, for example, five drugs, the drug with the

earliest market authorization was used for the calculation of the variable[6]. The statistics for the *QUAL* variable shows, that for around half of the entries additional benefit was observed.

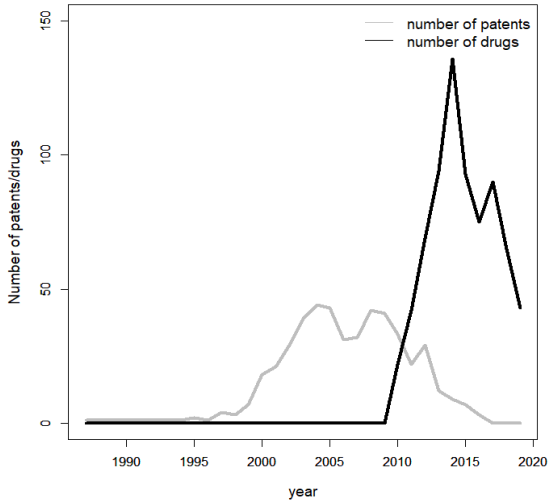


Figure 3: Number of products and patents per year

Source: own calculation

As product dataset was collected for the period 2010-2019, the number of products before 2010 is equal to zero.

Table 2: Descriptive statistics, dependent variables

	Obs	Mean	St.dev	Min	Median	Max
TIME	463	8,844	4,181	1,000	8,000	22,000
QUAL	463	0,433	0,496	0,000	0,000	1,000

Table 3 shows descriptive statistics and correlations for numeric independent and control variables. Additional exploration of the variance inflation factor has shown no multicollinearity issue for any variable.

The descriptive statistics of variables of interest shows that less than ¼ of patents are developed by inventors representing different countries, and less than 1/10 of patents have international applicants. The most common inventor countries are the USA with 56,55% of inventor entries[7], Great Britain with 14,92%, and Japan with 8,86%; the most

[6] Additionally, the year of priority patent application was considered. Thus, the maximum time between application and authorization of 22 years was achieved.

[7] This includes only one inventor-patent or applicant-patent combination, as one inventor/applicant may be attached to more than one patent.

common applicant countries are the USA with 40,66% of applicant entries, Great Britain with 19,70%, and Switzerland with 9,68%.

Additionally, only 7% of patents include SME as an applicant, which is a widespread tendency of the pharmaceutical industry or biotechnology, and corresponds to the general structure of the field (see e.g. Häussler 2007, Kahl 2015). Interestingly, only half of the patents have an applicant, that is also market authorization holder. Such statistics corresponds with Svensson (2012), who observed the patent commercialization by the original firm in only 45% of the cases. The reason behind this discrepancy may lie in the patents' acquisition and licensing agreements or relate to the situation, when a patent is applied for by a subsidiary and commercialized by a headquarter. Last, the relatively high average family size of the patent (32,49) indicates the importance of the patents in question for the company.

Table 3: Descriptive statistics and correlations, independent and control variables

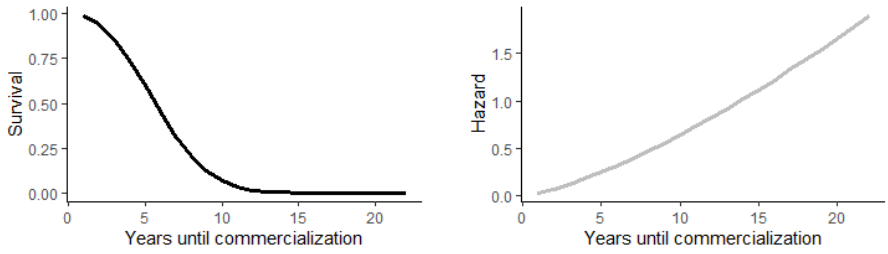
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NOINV (1)	1,000						
NOAPPL (2)	0,013	1,000					
CTRINV (3)	0,116**	0,224***	1,000				
CTRAPPL (4)	0,026	0,768***	0,317***	1,000			
FAMSIZE (5)	0,148***	0,064	0,017	0,046	1,000		
APPLAUTH (6)	0,085*	0,050	0,056	0,041	-0,009	1,000	
SME (7)	0,018	0,054	0,101**	0,024	-0,061	-0,187***	1,000
Obs	463	463	463	463	463	463	463
Mean	5,576	1,120	0,221	0,071	32,490	0,501	0,069
st.dev	4,576	0,338	0,415	0,257	22,437	0,501	0,253
Min	1,000	1,000	0,000	0,000	0,000	0,000	0,000
Median	4,000	1,000	0,000	0,000	32,000	1,000	0,000
Max	41,000	3,000	1,000	1,000	158,000	1,000	1,000

*** p<0,01; ** p< 0,05; * p<0,1

4.2. Analysis of speed and success of commercialization

First, the results of the analysis of the timing of patent commercialization are presented. Figure 4 shows survival and baseline cumulative hazard functions of the full patent dataset. Figure 4 shows the probability of commercialization, indicated by product market authorization in the t^{th} year after patent priority application, conditional upon no commercialization having occurred in *t-1*. It can be seen, that commercialization occurs quite fast with around 40% commercialization probability for patents up to five years after their priority application. Furthermore, fifteen years after priority application the commercialization probability is close to zero. However, as there are no

uncommercialized patents in this dataset, the cumulative hazard of being authorized increases with time, which is shown by the right figure (Jachno et al. 2021).



Survival function *Baseline cumulative hazard function*

Figure 4: Patent and product statistics

Source: own calculation

Table 4 shows the results of the Weibull AFT model estimations. the results of the Weibull AFT model estimations. Models 1-4 include only one variable of interest each plus control variables, whereas Model 5 includes all variables of interest as well as control variables. Additionally, Model 6 presents robustness checks with the use of ordinary least squares regression, including all variables[8]. A positive coefficient of the Weibull AFT model indicates the deceleration of the market authorization and a negative coefficient indicates its acceleration.

As can be observed, increased number of applicants lead to slower market authorization of the underlying patent. This confirms Hypothesis 1. The reason for that may lie in coordination costs, as outlined by Bercovitz & Feldman (2011). When two or three actors are involved in the patent creation, the negotiations regarding the patent implementation and commercialization may be overcomplicated. Furthermore, the results demonstrate that the presence of international applicants leads to slower market authorization of the patent, as was stated in Hypothesis 3, although this effect is no longer significantly present when all variables were included. This result goes in line with the analysis of Huang et al. (2018) which showed the high transaction costs of negotiating patents when international actors are involved. This may also include the necessity of knowledge about different legal conditions of different drug authorization agencies. This intuition is supported by the fact, that the time between patent application and market authorization decreases significantly if the patent applicant is also market authorization holder, as in this case negotiation costs are absent.

In contrast, the number of inventors per patent does not have any impact on the speed of patent market authorization, which corresponds to the results of Svensson

[8] Checks for Models 1-4 are available in the appendix.

(2012) and contradicts Hypothesis 2. The reason behind it may be that applicants and not inventors usually make the decisions regarding patent market authorization. However, international inventors seem to decelerate market authorization of the related drugs, which contradicts the results of Huang et al. (2018) and, thus, Hypothesis 4. This may also be caused by coordination costs, related to product development with geographical distance, which complicates the application of diverse knowledge necessary to create a patent-related drug. Additionally, a larger patent family significantly decelerates the speed of market authorization. Larger patent families may indicate broader inventions or patents, they also reflect the situation when a firm seeks patent protection in many countries. In this case, firms, especially large ones, may act strategically via prudently protecting specific inventions, even though the connected product is far from being created

Table 4: Weibull hazard model estimations

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
NOINV	-0,002	-	-	-	-0,002	0,020
	(0,015)				(0,005)	(0,042)
NOAPPL	-	0,176***	-	-	0,228**	2,197**
		(0,061)			(0,092)	(0,853)
CTRINV	-	-	0,098*	-	0,089*	0,947**
			(0,051)		(0,052)	(0,467)
CTRAPPL	-	-	-	0,143*	-0,132	-1,599
				(0,084)	(0,128)	(1,160)
FAMSIZE	0,004***	0,004***	0,004***	0004***	0,004***	0,037***
	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,008)
APPLAUTH	-0,112***	-0,125***	-0,126***	-0,126***	-0,129***	-1,218***
	(0,043)	(0,043)	(0,044)	(0,044)	(0,044)	(0,392)
SME	0,026	0,011	0,000	0,015	-0,002	0,255
	(0,082)	(0,081)	(0,082)	(0,081)	(0,082)	(0,750)
ATC [9] Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2,137***	1,950***	2,130***	2,143***	1,889***	4,899***
	(0,074)	(0,097)	(0,072)	(0,073)	(0,124)	(1,121)
Obs	455	455	455	455	455	455
Log Likelihood	- 1.290,271	- 1.285,782	- 1.288,412	- 1.288,786	- 1.284,054	R^2 adj 0,143
chi²	55,196***	64,173***	58,912***	58,164***	67,629***	F statistic 4,894***

*** p<0,01; ** p< 0,05; * p<0,1, standard errors in parentheses

[9] Following ATC dummies appeared to be significant (all decelerate the market authorization): B - Blood and blood forming organs; G - Genito urinary system and sex hormones; M - Musculo-skeletal system; R - Respiratory system.

Table 5 shows the results of the probit model estimations for the success variable. Here again, Models 1-4 include only one variable of interest each plus control variables, whereas Model 5 includes all variables of interest as well as control variables. As already noted earlier, veterinary products were excluded from the sample for this analysis because of the absence of data on early benefit assessment. Thus, 455 patent entries remained in the dataset.

The only hypothesis that can be supported here is Hypothesis 6, indicating that the number of inventors positively influences the quality of the related product, which also corresponds to previous findings (e.g. Singh & Fleming 2010). Thus, combining knowledge of many inventors inside one team may favourably impact not only patent quality, but also the quality of the resulting product. However, contrary to literature-based hypothesis 8, no impact of international inventors could be found. Also, the size and the number of countries of the applicant team do not impact the quality of a resulting product. Thus, hypotheses 5 and 7 cannot be supported. This data indicates that, the success of a product is mostly connected to inventor team composition.

Table 5: Probit model estimations

	Model 1	Model 2	Model 3	Model 4	Model 5
NOINV	1,042***	-	-	-	1,044***
	(0,015)				(0,015)
NOAPPL	-	1,138	-	-	1,157
		(0,190)			(0,295)
CTRINV	-	-	0,962	-	0,893
			(0,156)		(0,164)
CTRAPPL	-	-	-	0,588	1,029
				(0,253)	(0,403)
FAMSIZE	0,995	0,996	0,996	0,996	0,995*
	(0,003)	(0,003)	(0,003)	(0,003)	(0,003)
APPLAUTH	0,958	0,993	1,005	0,995	0,960
	(0,137)	(0,136)	(0,136)	(0,136)	(0,138)
SME	0,814	0,860	0,880	0,870	0,809
	(0,285)	(0,284)	(0,284)	(0.282)	(0,290)
ATC[10] Dummies	Yes	Yes	Yes	Yes	Yes
Constant	0,525***	0,513**	0,530**	0,588**	0,809**
	(0,234)	(0,300)	(0,230)	(0,230)	(0,388)
Obs	467	467	467	467	467
log likelihood	-268,429	-272,278	-272,487	-272,389	-267,919

*** p<0,01; ** p< 0,05; * p<0,1, standard errors in parentheses

[10] Following ATC dummies appeared to be significant (all positively impact success of the product): B - Blood and blood forming organs; H - Systemic hormonal preparations, excl. sex hormones and insulins; L - Antineoplastic and immunomodulating agents; M - Musculo-skeletal system.

5. Discussion and conclusion

This paper focuses on the impact of applicant and inventor team characteristics on the speed of market authorization of patent-related products and the quality of these products. Considering gaps in the existing literature on the importance of inventor and applicant team composition for the success of created inventions (Gay et al. 2008, Singh & Fleming 2010) and for patent transfer activities (Svensson 2012, Huang et al. 2018, Li & Rizzo 2020) in the broad sense, this paper focuses on the impact of the composition of inventor and applicant teams on the commercialization in form of product authorization.

Results of this paper reveal the impact of applicant and inventor team characteristics not only on the success of the resulting product but also on the speed of product market authorization. The analysis is performed on the example of the European pharmaceutical industry, which is receiving increasing attention in the face of global challenges. Thus, fast and qualitatively high developments of the pharmaceutical industry are necessary to reach the SDG3, proclaimed by the United Nations, which aims for good health and well-being.

For the analysis, a unique manually created dataset was applied, which combines product data, taken from the EMA, with related patent data, acquired via Pat-INFORMED from WIPO and Patent Register from Health Canada. The final dataset includes 467 patents.

The results of the survival and probit analysis reveal discrepant results. Generally, it can be stated, that inventors mostly impact the quality of the patent-related product and applicants influence the speed of market authorization of the patent. It was revealed that larger applicant teams and the presence of international applicants slow down the process of market authorization. The reason for that may lie in the negotiation and coordination costs, which occur when more than one applicant is connected to the invention (Bercovitz & Feldman 2011; Filiou & Golesorkhi 2016). Additionally, international inventors decelerate the speed of market authorization, probably for similar reasons.

For the case of product quality, the results of the analysis indicate a positive impact of the number of inventors on the early benefit assessment of the product. The reason behind this might be the combination of different knowledge bases of inventors. However, no impact of the applicant team on the product quality was found, indicating that these are mostly inventors who are responsible for patent and subsequent product success.

There are several limitations to this analysis. First, the survival analysis is based on the number of years between priority patent application and market authorization. Even though market authorization is widely used as a product introduction timestamp, the duration of clinical trials varies for different subfields in the industry (Wagner & Wakeman 2016). Thus, it could be important to include the date of different phases of clinical trials to the analysis. This, however, requires additional investigation of the EMA website, as

this data is not directly available on a product summary. Further, sometimes inventors from different organizations may appear on the patent in the inventor team without reflection of these organizations among applicants. Thus, additional manual checks for inventor affiliations could be needed to refine the number of applicants for a patent (*NOAPPL*) variable. However, it could be stated that not all patent documents contain direct inventor affiliations. Additional explorations could also be done regarding the biography of inventors in order to add several independent variables to the analysis. Furthermore, the success variable could include related sales volumes or product demand could be added to future analyses, in order to focus on the market side of product success.

Some of the possible extensions were already covered by the robustness checks. Thus, the applicant and inventor country variables were given the value of one, if any applicant or inventor comes from a different country than other ones. More differentiation in these variables may be necessary. For example, if inventors or applicants represent neighbouring countries (e.g. US/CA, FR/IT, DE/AT teams), the coordination costs regarding market authorization of the invention may be different than for the case of geographically distant partners. Thus, an additional analysis was performed, where variables were given the value of zero, if inventors or applicants represent neighbouring countries and one otherwise. The results of this analysis were, however, similar to the results of the main analysis of this paper. Additionally, square terms of the number of applicants and inventors were included in the analysis; however, they appeared insignificant.

Despite these limitations, this study has overarching implications. Thus, it adds to the literature on patent to product transition by focusing on applicant and inventor team characteristics. It also shows managers and policy makers the impact of different knowledge bases and larger inventor teams on the quality of the patent, thus, promoting the organizational learning and talent acquisition. Specifically, in current times, when quick and high-quality solutions in the medical field are gaining extreme importance, managers of pharmaceutical companies should be aware of the impact of the combination of knowledge bases of their employees for the subsequent product success. Additionally, practitioners should not be afraid to focus on the inventive power of their own employees. The results, however, may be true not only for the pharmaceutical industry, but also for other fields requiring complex knowledge: e.g., photovoltaics, automotive, or semiconductor industry (e.g. Hipp & Binz 2020).

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Appendix

A1: ATC Classification statistics for complete product dataset

ATC Classification	Number of Products
A - Alimentary tract and metabolism	81
B - Blood and blood forming organs	44
C - Cardiovascular system	32
D – Dermatologicals	6
G - Genito urinary system and sex hormones	22
H - Systemic hormonal preparations, excl. sex hormones and insulins	10
J - Antiinfectives for systemic use	91
L - Antineoplastic and immunomodulating agents	197
M - Musculo-skeletal system	20
N - Nervous system	83
P - Antiparasitic products, insecticides, and repellents	1
R - Respiratory system	131
Empty	3

A2: OLS robustness checks

	Model 1	Model 2	Model 3	Model 4
NOINV	0,027 (0,042)	-	-	-
NOAPPL	-	1,506*** (0,559)	-	-
CTRINV	-	-	1,027** (0,447)	-
CTRAPPL	-	-	-	1,052* (0,747)
FAMSIZE	0,039*** (0,008)	0,038*** (0,008)	0,039*** (0,008)	0,039*** (0,008)
APPLAUTH	-1,083*** (0,393)	-1,145*** (0,390)	-1,141*** (0,391)	-1,099*** (0,392)
SME	0,617 (0,751)	0,452 (0,747)	0,448 (0,750)	0,582 (0,749)
ATC [11] Dummies	Yes	Yes	Yes	Yes
Constant	7,291*** (0,673)	5,819*** (0,873)	7,234*** (0,662)	7,389*** (0,663)
Obs	467	467	467	467
R^2 adj	0,125	0,138	0,135	0,128
F statistic	4,927***	5,404***	5,266***	5,037***

*** p<0,01; ** p< 0,05; * p<0,1, standard errors in parentheses

A3: Log-likelihoods for different AFT distributions (full model)

Distribution	Log-likelohood
Weibull	- 1.284,054
Exponential	- 1.475,137
Log-logistic	- 1.311,364
Log-normal	- 1.322,226

[11] The following ATC dummies appeared to be significant (all decelerate the market authorization): B - Blood and blood forming organs; G - Genito-urinary system and sex hormones; M - Musculo-skeletal system; R - Respiratory system.

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