sustainability

MDPI

Article

Factors Affecting Pricing in Patent Licensing Contracts in the Biopharmaceutical Industry

Jeong Hee Lee [1], Eungdo Kim [1,*], Tae-Eung Sung [2,*] and Kwangsoo Shin [1]

[1] Graduate School of Health Science Business Convergence, College of Medicine, Chungbuk National University, Cheongju 28644, Korea; smartbio@naver.com (J.H.L.); sksidea@chungbuk.ac.kr (K.S.)

[2] Department of Computer and Telecommunications Engineering, College of Science and Technology, Yonsei University, 1 Yonseidae-gil, Wonju 26493, Gangwon-do, Korea

* Correspondence: edkim@chungbuk.ac.kr (E.K.); tesung@yonsei.ac.kr (T.-E.S.); Tel.: +82-010-9059-1931 (E.K.); +82-010-7533-5407 (T.-E.S.)

Received: 26 June 2018; Accepted: 31 August 2018; Published: 3 September 2018

Abstract: This paper analyzes factors affecting pricing in patent licensing contracts in the biopharmaceutical industry based on a dataset that includes royalty-related data such as running royalty rate, up-front payment, milestones, and deal value. Data on drug candidates for 11 drug classes is obtained for regression analysis between royalty-related data and multiple input descriptors such as market factors, licensor factors, and licensee factor in order to derive the formula for predicting royalty-related estimates such as royalty rate, up-front payment, milestones, and deal value. Data is gathered from multiple sources including MedTrack and is processed through merging and cleaning. We found that the three most important factors in pricing in patent licensing in the biopharmaceutical industry are CAGR (Compound Annual Growth Rate), PDELR (Previous Deal Experience of Licensor), and AR (Attrition Rate). We found that factors in the formula used to estimate the license fee are totally different by drug class. We found that the three most important factors in the frequency in the formula used to estimate the license fee are PDELR, RnDLR (R&D Costs of Licensor), and PDELE (Previous Deal Experience of Licensee). This study suggests a method of estimating the proper royalty rate, up-front payment, milestones, and deal value of the drug candidates of 11 drug classes by using easily obtained input data.

Keywords: valuation; licensing deal; drug class; royalty rate; up-front fee; milestones; deal value; regression; biotech industry; attrition rate

1. Introduction

Drug development is expensive and risky because it requires a lot of time and money from an initial concept to approval [1,2]. Licensing is recognized as a good exit strategy to overcome the economic crisis in biotech companies and royalties are recognized as one of the major revenue sources in the biotech industry [3,4]. Therefore, the number of licensing transfers in the biotech industry is at least 10 times that of other industries [5,6].

Valuation for the drug under development is required for various purposes including merger and acquisition (M&A) transaction and two major quantitative valuation approaches are applied in the biotech industry, that is the discounted cash flow (DCF) method and the real options method [7,8]. The risk-adjusted Net Present Value (rNPV) method is an NPV method that uses only the attrition rate at development stage as a discount rate to consider the risk at each development step and was developed to overcome the disadvantages of DCF and real options methodology. The rNPV method, which considers the drug type as well as the development phase, recently emerged [9], but it is

not enough to reflect the characteristics of the biotech industry and to provide accurate valuation for early-stage drugs. Paik's study confirmed that technology providers (licensor) and technology adopters (licensee) differ in factors that are important to technology transfer, while past studies tend to focus on only one type of licensors/licensees [10,11].

The purpose of this study is (1) to identify the factors that affect each license fee through previous studies, (2) to analyze the effect of each factor on the license fee by multiple regression, and (3) to make a formula through the values of the influencing factors by drug class by using backward elimination method.

The biotech industry is facing a challenging situation with decreasing financial performance and declining R&D productivity. Licensing has become an important element of the business model in the biotech industry and a key activity for biotech companies and determining the right royalty rate in licensing deal is very important to pharmaceutical and biotechnology success. The valuation is vital to valuate the technology in finding licensing partner, fundraising for further development, portfolio management in biotech industry [12]. The value of technology depends on a number of factors in licensing deal between technology provider and technology consumer [6]. Main technology providers (licensors) are biotech, academia including national research institutes. Main technology consumers (licensees) are pharma company and biotech [12]. This study is meaningful to provide royalty-related estimates such as royalty rate, up-front payment, milestones, and deal value by drug class based on historical deal data in more simple way. The existing valuation methods like DCF and the real options require long time more than one month and complex steps to derive these royalty-related estimates. Licensing deals between pharmaceutical companies and biotech/academia are active in the biotechnology area [8].

The types of factors in view of β (Non-standardized regression coefficients) that influence all aspects of the license fee including deal value, royalty rate, upfront payment, milestones is as follows: ① CAGR (Compound annual growth rate) ② PDELR (Prior Deal Experience of Licensor) ③ AR (Attrition Rate) ④ RNDLR (Licensor R&D Costs) ⑤ RNDLE (Licensee R&D Costs) ⑥ SALESLR (Licensor Sales) ⑦ SALESLE (Licensee Sales). In fact, these factors can be later determined in order (the rank of influencing weights) since we investigate the correlation between the predictor and the dependent variables, leading to the size of regression coefficients. We found that the three most important factors in pricing in patent licensing in the biotech industry are CAGR, PDELR, and AR. We found that factors in the formula used to estimate the license fee are totally different by drug class. Total frequency of factors in the formula to estimate all the technical fee including deal value, royalty rate, upfront payment, milestones by drug class is as follows: ① PDELR (22 times) ② RNDLR (16) ③ PDELE (15) ④ SALESLE, CAS (14) ⑤ AR (9). We found that the three most important factors in the frequency in the formula used to estimate the license fee are PDELR, RNDLR, and PDELE.

This rest of this paper is organized as follows. The second section reviews licensing in the biotech industry and the development status of the valuation method. The third section describes the proposed research framework. The fourth section presents the data, empirical model, and results. The final section contains the discussion and implications.

2. Literature Review

2.1. Licensing in the Biopharmaceutical Industry

The discovery and development of new drugs is a highly risky investment because it is a lengthy and expensive process. Few companies have the capability to develop products from the discovery of a new lead compound to delivering the approved drug to patients. Even those that do have the capability may not have the capacity to have pipelines that are broad enough to provide a smooth flow of new drugs [6]. Small pharmaceutical biotech companies with good technology generally have limited R&D budgets and drug development periods are so long that they are often close to budgetary crisis, which makes licensing a good strategy and business model to overcome monetary crisis [3,13].

Licensing between competing firms is popular in many countries. Several papers have focused on the horizontal product differentiation approach. Using this approach, Erkal (2005) finds that royalty licensing is always profitable for the licensor regardless of its technological lead over the competitor. Furthermore, when the technology gap between competing firms is small, it is socially optimal to discourage licensing. Sinha (2010) shows that when licensing takes place between a multinational and a domestic firm, if FDI (Foreign Direct Investment) is the multinational's mode of entry into the domestic market, royalties are more profitable compared to fixed fee licensing [14].

2.2. Development of Valuation Method

Value is established through trade and is dependent on market supply and demand as well as other factors. Essentially, value is the amount that both the buyer is willing to pay and the seller is willing to accept. Both sides will be interested in achieving the best deal and will want to know what other buyers might pay or sellers accept. Comparable products or technologies that have recently been traded may provide an indication of the expected value. The value of technology depends on many factors. There will be more than a dozen variables in even the simplest eNPV (Expected Net Present Value) model for a product in early clinical development. These include the size of the target market for the final therapeutic product, the anticipated clinical qualities of the drug, and the extent of competition for the drug and these will include the phase-specific success probabilities, development costs and timelines, the expected market size and market share, the costs of goods, and marketing and administration [6].

Ruckman and McCarthy examined the determinants of licensing using 93 licensing agreements in the global biopharmaceutical sector in a panel dataset spanning 1993–2007 and found that licensors with strength in technological prestige, licensing experience, and combined technological depth and breadth are more likely to license-out their patents and have a greater chance of being chosen by licensees [15].

Research on technology transfer has been carried out mainly through analysis of policy factors, factors for promoting technology transfer, and ways to promote the success of technology transfer. According to a recent study by Hwhang (2015), it was found that technology transfer through exploration of potential demand is more effective than 33 government-sponsored research institute technologies [16].

Understanding how fees or compensations are determined in patent licensing contacts is a critical issue for firms trying to profit from their inventions as well as for firms that source technology. Patent licensing has become an increasingly widespread practice [17,18].

Patent licensing is particularly important for companies that have limited resources to commercialize their own inventions. Companies may choose licensing if the invention falls into areas that are not core to their business. The licensing of patents has also become an important concern for universities, which have been encouraged to profit from their own inventions since the Bayh-Dole Act of 1980 gave universities the right to own and license inventions resulting from federally-funded academic research. Several explanations for the phenomenon of patent under exploitation have been suggested, including managerial myopia, inertia, management incompetence [18], the marginality and low value of patents, and transaction costs or other impediments in the technology market [19].

The valuation of patents has caught widespread attention in innovation research because patents are one of the few readily available measures of research output. Mariko (2010) added the proximity of a licensed patent to a licensor's core technology (the number of a licensor's patents in the same IPC as the licensed patent compared to the total patent stock of the licensee), licensor patent stock (the number of patent applications by a licensor), and licensee patent stock as the determinants of the price of patent licensing. Sakakibara's research added the sales per capital of licensor and licensee as a size indicator among the determinants of the price of patent licensing [11]. However, due to the limited availability of data, past studies typically used proxies for the value of patents, such as citations [20], Tobin's Q [20,21], patent renewal [20], and patent litigation costs [22]. Scherer and Harhoff [23] and

Gambardella et al. [24] use a survey-based measure. Research based on actual patent transaction data such as survey-based research [25], examination of those contract features which do not include pricing [17], and studies of university patents [26,27] is very limited. Patents without established market values (e.g., no negotiated royalty rates) are often valued by comparing the number of citations the patent has received to those received by other patents whose market values are established. Caviggioli and Ughetto (2013) investigated the main drivers of companies' decisions to engage in patent licensing and sales transactions and then examined how improvements in the marketplace for patents and more intense involvement of patent brokers might impact the factors hindering the development of patent transactions [28]. For recently issued patents, which have not had time to accumulate citations, this [29].

Determining a reasonable royalty rate for a licensing deal is very challenging, and proper valuation is essential to make a reasonable determination. There are two major valuation approaches used in the field of life sciences: discounted cash flow (DCF) and real options [1]. The valuation methodology for new drug pipelines includes rNPV or eNPV (expected NPV) or the probability-adjusted NPV method in which technical risk is reflected on the cash flow, the scenario-implemented decision tree method, which calculates the weighted average NPV according to the probability of specific scenarios, and real options, which is often used by financial professionals but is not favored by drug experts. The rNPV method is most frequently used in practical work in the field of life sciences [1]. Attrition rates proposed by DiMasi [30] are most often used for valuation among technology traders in biotechnology and pharmaceutical companies. A recent study by Thomas, D.W. et al. derived the attrition rate at each development stage for four drug types [9].

Lee et al. suggested a method of estimating the proper royalty rate and up-front payment using the formula derived from the regression of a dataset of historical licensing data [1]. However, further in-depth research is necessary to investigate the relationship between royalty-related data and more input variables that can be converted to numerical value and can be used for the input for prediction [1]. Lee's study group suggested a method of estimating the proper royalty rate and up-front payment using multiple data descriptors. In the regression analysis study on Anticancer activity candidates, factors that influence the royalty rate are ranked as follows: (1) Licensee Revenue (+) (2) Market Size (−) (3) TCT median value (−) (4) CAGR (−) (5) Attrition Rate (+). In the regression model to predict the royalty rate, Royalty Rate is directly proportional to Licensee Revenue and Attrition Rate and Royalty Rate is inversely proportional to Market Size, TCT median value, and CAGR [8].

Byeon (2013) studied the influence of factors on the outcome of the technology trading contract. The positive order of influence on the success of the technology trading contract was found to be the technical transaction environment factor, ability, and the [31]. Jong-ilBaek and Byung-hwan Hyun (2017) analyzed the priority factors of technological, marketability, internal factors, and technical supply agencies, which act as complex variables in license fee negotiation, using AHP analysis from the viewpoint of licensee [32]. Another study by Jong-ilBaek and Byung-hwan Hyun study (2017) shows that both parties including the government-funded research center and private company acknowledge "Technical considerations for determining the profitability of the technologies" and "The interest and willingness of the management group" as critical factors for the determinants of royalties. The difference between the parties is that private companies acknowledge "Available budget plan" as a critical factor while government-funded research centers value "Market competitiveness" [33].

3. Research Framework

Paik's study separated licensor and licensee when considering the factor influencing technology transfer, while past studies tend to focus on only one type of licensors or licensees [10,11]. The rNPV method became the major valuation approach since DiMasi suggested the attrition rate at development stage as a factor for valuation in the biotech industry [1,3,8,10,34–37]. According to Baek's study, Market Size and CAGR were the major factors to estimate the running royalty in the biotech industry [8,32,33].

Figure 1 presents the framework to research factors affecting pricing in patent licensing contracts in the biopharmaceutical industry.

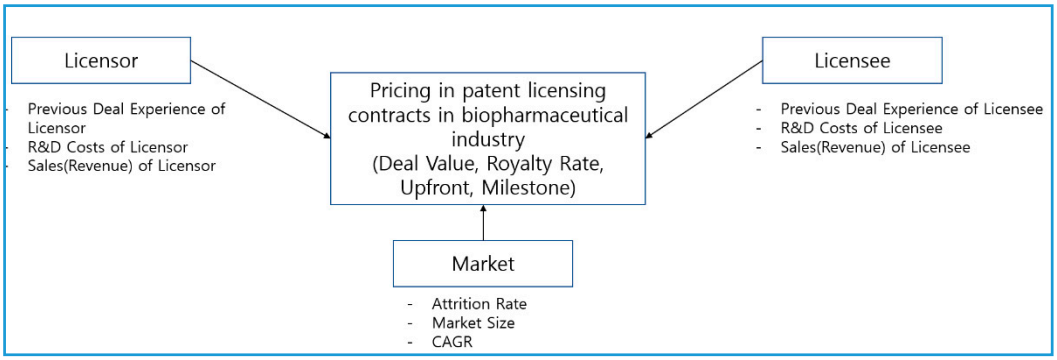

Figure 1. Factors affecting pricing in patent licensing contracts in the biopharmaceutical industry.

3.1. Market

The attrition rate at development stage was proposed by DiMasi's study [30] and is used most often for the valuation in the biotechnology industry. According to Baek's study, Market Size and CAGR were the major factors to estimate the running royalty in the biopharmacuetical industry [33] and several studies followed [8,32].

3.2. Licensor

The licensor seeks to extract value in the form of licensing revenues and may be motivated to license-out their technologies because they lack the financial, physical, or intellectual resources to commercialize it [15]. Past studies tend to focus on only one type of licensor or licensee [11]. However, Paik's research confirmed that licensor and licensee differ in factors that are important to technology transfer, such as previous deal experience [10], and there have been several subsequent studies on licensor factors [38,39]. Svačina and several groups added R&D licensor costs as factors affecting the value of intangibles [18,40]. Sakakibara added the sales per capital of the licensor and licensee as a size indicator among the determinants of the price of patent licensing [11].

3.3. Licensee

Paik's research confirmed that licensor and licensee differ in factors that are important to technology transfer, such as previous deal experience [10], and several studies for licensee factor followed [31,38,40]. Pavel Svačinaand several groups added the R&D costs of licensee to as the factors affecting the value of intangibles [18,41]. Sakakibara added the sales per capital of the licensor and licensee as a size indicator among the determinants of the price of patent licensing [11].

4. Methodology

4.1. Empirical Model

We employed linear regression model like the `followings`. Technical Fee is a dependent variable and PDELR, PDELE, MS, CAGR, AR, RNDLR, SALESLR, RNDLE, SALESLE are independent variables.

Model I.

$$\text{Technical Fee}_i = a_1 \times \text{PDELR} + a_2 \times \text{PDELE} + a_3 \times \text{MS} + a_4 \times \text{CAGR} + a_6 \times \text{AR} + a_7 \times \text{RNDLR} + a_8 \times \text{SALESLR} + a_9 \times \text{RNDLE} + a_{10} \times \text{SALESLE} + u_i$$

where u_i is the error term.

4.2. Data

Data is gathered from multiple sources such as MedTrack and Harvard WRDS (Wharton Research Data Services) for analysis and is processed through merging and cleaning.

Data collection is based on the following resources: ① DV (Deal Value), RRA (Royalty Rate Average), MP (Milestone payments), TU (Total Upfront Payment), PDELR(Prior Deal Experience of Licensor), PDELE (Prior Deal Experience of Licensee), AR (Attrition Rate) by Development Phase from MedTrackdatabase (Informa UK Limited); ② MS (Market Size), CAGR (Compound Annual Growth Rate) for drug class, several market reports from Global View Research, Grand View Research, IndustryARC, Transparency Market Research, EvaluatePharma, and QuintilesIMS Institute [42–47]; ③ RNDLR (R&D Costs of Licensor), CAS (Sales of Licensor), RNDLE (R&D Costs of Licensee), SALESLE (Sales of Licensee), Harvard WRDS (Wharton Research Data Services) database and MedTrack database (Informa UK Limited).

4.3. Variables

In general, we should consider whether control variables influence the relation between independent and dependent variables. To investigate various factors affecting the deal values of the licensing contract, at first, we introduced potential candidates for control variables such as whether the licensee is a large firm or small-and-medium size firm (which is categorized to nominal variables). But in this work, we put all potential control variables to the subset representing independent variables, because we found no influence effect in that there exists no statistical significance without showing no cases less than significance level of 0.05 (5%) even if we fix one for control variable and remain the rest for independent variables.

In case of PDELR, PDELE, we calculated the number of deals prior to the deal date. In case of RNDLR, SALESLR, RNDLE, SALESLE, we used the value of the previous year based on the deal date. DiMasi's attrition rate [30] is applied for the development phase and the average royalty rate is used after data cleaning.

Table 1 presents the category, criteria, and related studies of each variable and Table 2 describes the statistical characteristics of independent variables

Table 1. Summary of variables.

Categories		Variables	Descriptions	References
Dependent variables		[DV]	Deal Value (M$)	[48–50]
		[RRA]	Royalty Rate Average (%)	[1,8,29,32,35–39,51–54]
		[MP]	Milestone payments (M$)	[54–56]
		[TU]	Total Upfront Payment (M$)	[1,8,54,56]
Independent variables	Market	[MS]	Market Size (B$)	[1,8,34]
		[CAGR]	Compound Annual Growth Rate (%)	[1,8,34]
		[AR]	Attrition Rate (%)	[1,8,10,33–38]
	Licensor	[PDELR]	Previous Deal Experience of Licensor (times)	[10,15,39,41]
		[RnDLR]	R&D Costs of Licensor (M$)	[3,16,37,39,54,55,57,58]
		[SalesLR]	Sales (Revenue) of Licensor (M$)	[11,15,36,54]
	Licensee	[PDELE]	Previous Deal Experience of Licensee (times)	[10,31,39,43]
		[RnDLE]	R&D Costs of Licensee (M$)	[18,32,41]
		[SalesLE]	Sales (Revenue) of Licensee (M$)	[11,15,37,59]

Table 2 presents the statistics of independent variables.

Table 2. Statistical characteristics of independent variables.

	Mean	Min	Max	Std. Dev.
1. PDELR	30.89	0	145	30.73
2. PDELE	13.50	0	75	15.40
3. MS	82.88	50.1	125.5	16.09
4. CAGR	8.56	0	10.9	3.02
5. AR	35.56	13.3	93	25.01
6. RNDLR	1657.0	0	7680.0	2349.7
7. SALESLR	11,439.4	0	61,095.0	16,487.4
8. RNDLE	715.01	0	9431.0	1780.2
9. SALESLE	4274.4	0	65165	11,472.2

5. Results

5.1. Regression Analysis of Total Dataset

As one of the most popular regression methods in use, we hereby employed the regression analysis of "Enter method" in Table 3 but found that most of the variables returned beyond the significance level, except for specific metrics such as "PDELR, CAGR, RNDLR, SALESLR, RNDLE" (for DV) and "PDELR, CAGR, RNDLR, SALESLR" (for MP).

Table 3. Descriptive statistics for technical fee factors (Enter Method).

Dependent var.	**DV**		**RRA**		**TU**		**MP**	
***p*-value (Model)**	0.000000		0.022684		0.000027		0.000000	
# of sample	**472**		**247**		**355**		**251**	
Statistical coeff.	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**
Constant	−22.330436	0.826584	6.511484	0.02 Development of a technolog78	7.547157	0.744175	105.381210	0.562632
Indep, Var.								
PDELR	5.851656	0.000000	0.037060	0.049948	0.037060	0.049948	8.334518	0.000000
PDELE	−1.115316	0.445753	0.000625	0.984304	0.000625	0.984304	−2.602873	0.247456
MS	1.428798	0.135370	0.044159	0.088184	0.044159	0.088184	−1.827841	0.347045
CAGR	17.829881	0.004327	0.151523	0.365859	0.151523	0.365859	29.316390	0.004722
AR	−1.813374	0.011470	0.039696	0.039477	0.039696	0.039477	−1.058399	0.388484
RNDLR	0.182640	0.000008	−0.000201	0.865463	−0.000201	0.865463	0.283853	0.000013
SALESLR	−0.028755	0.000001	0.000010	0.957381	0.000010	0.957381	−0.045430	0.000001
RNDLE	0.139317	0.033789	−0.004327	0.008315	−0.004327	0.986540	0.011289	0.913720
SALESLE	−0.015412	0.127446	0.000682	0.010247	0.000853	0.682485	0.001756	0.911336

Thus, we applied to an alternative of "Backward elimination method" in Table 4, which might be well-known as to provide high fidelity to model fitness and "metric significance" and much more appropriate for our work.

Table 4. Descriptive statistics for technical fee factors (Backward method).

Dependent var.	**DV**		**RRA**		**TU**		**MP**	
***p*-value (Model)**	0.0000000		0.002573		0.0000010		0.0000000	
# of sample	**472**		**247**		**355**		**251**	
Statistical coeff.	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**
Constant	70.773093	0.3138740	12.74085	0.0000000	159.46549	0.0001630	−95.645835	0.3085800
Indep, Var.								
PDELR	5.91506	0.0000000	0.03654	0.0444820	7.8125	0.0000000	8.039028	0.0000000
PDELE								
MS								
CAGR	19.758378	0.0014660					29.228961	0.0027440
AR	−1.963919	0.0060120						
RNDLR	0.176483	0.0000140			0.272934	0.00002	0.297096	0.0000030
SALESLR	−0.028014	0.0000020			−0.043594	0.0000030	−0.046986	0.0000000
RNDLE	0.038596	0.0055600	−0.00458	0.0046740				
SALESLE	0.000735		0.000735	0.0053450				

From the results of multiple regression analysis, we did not find the occurrence of multicollinearity issues in that tolerances for all four cases (DV, Milestone, Royalty and Upfront) are no less than 0.1, and variable inflation factors (VIF) are no greater than 10.0. Thus, our models are justified without no collinearity problems.

Factors that influence the deal value are ranked as follows: ① CAGR (+) ② Prior Licensor Deal experience (+) ③ Attrition Rate (−) ④ Licensor R&D Costs (+) ⑤ Licensee R&D Costs (+) ⑥ Licensor Revenue (−). In the regression model to predict the deal value, deal value is directly proportional to CAGR, Previous Licensor Deal experience, Licensee R&D Costs, and deal value is inversely proportional to Attrition Rate and Licensor.

$$\begin{gathered}\text{Deal Value} = 70.773093 + 5.91506 \times \text{Previous Licensor Deal experience} + 19.758378 \\ \times \text{CAGR} - 1.963919 \times \text{Attrition Rate} + 0.176483 \times \text{Licensor R\&D Costs} - 0.028014 \times \\ \text{Licensor Revenue} + 0.038596 \times \text{Licensee R\&D Costs}\end{gathered} \quad (1)$$

Factors that influence the royalty rate are ranked as follows: ① Licensee R&D Costs (−) ② Licensee Revenue (+). In the regression model to predict the royalty rate, Royalty Rate is directly proportional to Licensee Revenue and Royalty Rate is inversely proportional to Licensee R&D Costs.

$$\text{Royalty Rate} = 12.74085 - 0.00458*\text{Licensee R\&D Costs} + 0.000735*\text{Licensee Revenue} \quad (2)$$

Factors that influence the Total Upfront Payments are ranked as follows: ① Previous Licensor Deal experience (+) ② Licensor R&D Costs (+) ③ Licensor Revenue (−). In the regression model to predict the total upfront payments, Total Upfront Payments is directly proportional to Previous Licensor Deal experience, Licensor R&D Costs and Total Upfront is inversely proportional to Licensee Revenue.

$$\begin{gathered}\text{Total Upfront} = 159.46549 + 7.8125 \times \text{Licensor Deal experience} + 0.272934 \times \text{Licensor} \\ \text{R\&D Costs} - 0.043594 \times \text{Licensor Revenue}\end{gathered} \quad (3)$$

Factors that influence Milestone payment are ranked as follows: ① CAGR (+) ② Previous Licensor Deal experience (+) ③ Licensor R&D Costs (+) ④ Licensor Revenue (−). In the regression model to predict the milestones, Milestones is directly proportional to CAGR, Previous Licensor Deal experience, Licensor R&D Costs and Milestones is inversely proportional to Licensor Revenue.

$$\begin{gathered}\text{Milestones} = (-95.645835) + 8.039028 \times \text{Previous Licensor Deal experience} + \\ 29.228961 \times \text{CAGR} + 0.297096 \times \text{Licensor R\&D Costs} - 0.046986 \times \text{Licensor Revenue}\end{gathered} \quad (4)$$

5.2. Regression Analysis of Deal Value by Drug Class

Based on the total dataset, we performed the regression analysis on deal value (dependent variable) by 11 drug class in Tables 5 and 6 and obtained the algebraic formulae sensitive to each drug class (independent variable) as below.

The formula to predict deal value by drug class is as follows.

(1) CV

$$\begin{gathered}\text{Deal Value} = 39.55697 - 2.408706 \times \text{Previous Licensor Deal experience} + 3.979936 \times \\ \text{Previous Licensee Deal experience} + 0.493004 \times \text{Licensor R\&D Costs} - 0.066841 \times \\ \text{Licensor Sales} - 0.119173 \times \text{Licensee R\&D Costs} + 0.025982 \times \text{Licensee Sales}\end{gathered} \quad (5)$$

(2) CNS

$$\begin{gathered}\text{Deal Value} = 69.271054 + 3.542896 \times \text{Previous Licensor Deal experience} + 4.322385 \times \\ \text{Previous Licensee Deal experience}\end{gathered} \quad (6)$$

(3) Derma

$$\text{Deal Value} = (-23.760665) + 13.174938 \times \text{Previous Licensor Deal experience} + 2.89314 \times \text{Previous Licensee Deal experience} - 0.624013 \times \text{Licensor R\&D Costs} + 0.05663 \times \text{Licensor Sales} - 0.127605 \times \text{Licensee R\&D Costs} + 0.049539 \times \text{Licensee Sales} \quad (7)$$

(4) EMGD

$$\text{Deal Value} = 151.407936 + 6.73419 \times \text{Previous Licensor Deal experience} - 0.079591 \times \text{Licensor R\&D Costs} \quad (8)$$

(5) GIM

$$\text{Deal Value} = 71.894673 + 9.989668 \times \text{Previous Licensor Deal experience} - 0.744804 \times \text{Licensor R\&D Costs} + 0.127621 \times \text{Licensor Sales} \quad (9)$$

(6) GU

$$\text{Deal Value} = 207.295828 + 0.01447 \times \text{Licensor Sales} - 22.968797 \times \text{Licensee R\&D Costs} \quad (10)$$

(7) Hema

There were five samples in the Haematology dataset, which was too small to perform the regression analysis.

(8) InI

$$\text{Deal Value} = 190.448746 + 0.150583 \times \text{Licensor R\&D Costs} + 0.10985 \times \text{Licensee R\&D Costs} \quad (11)$$

(9) Musk

There were six samples in the Musculoskeletal dataset, which was too small to perform the regression analysis.

(10) Onco

$$\text{Deal Value} = 230.734404 + 7.877775 \times \text{Previous Licensor Deal experience} - 2.758797 \times \text{Attrition rate} + 0.267436 \times \text{Licensor R\&D Costs} - 0.038537 \times \text{Licensor Sales} - 0.119173 \times \text{Licensee R\&D Costs} + 0.341313\text{\& Licensee R\&D Costs} - 0.04113 \times \text{Licensee Sales} \quad (12)$$

(11) Resp

$$\text{Deal Value} = 80.893396 - 3.085556 \times \text{Previous Licensor Deal experience} + 9.262484 \times \text{Previous Licensee Deal experience} + 0.174223 \times \text{Licensor R\&D Costs} - 0.016116 \times \text{Licensor Sales} + 0.214029 \times \text{Licensee R\&D Costs} \quad (13)$$

Table 5. Results of regression analysis of deal value by drug class (1).

Drug Class	CV		CNS		Derma		EMGD	
***p*-value (Model)**	0.0000000		0.0000000		0.0000000		0.012055	
# of sample	**22**		**93**		**23**		**36**	
Statistical coeff.	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**
Constant	39.55697	0.0050370	69.271054	0.0083770	−23.760665	0.0000000	151.407936	0.0058780
Indep, Var.								
PDELR	−2.408706	0.0227860	3.542896	0.0000000	13.174938	0.0000000	6.73419	0.0076750
PDELE	3.979936	0.0031190	4.322385	0.0000000	2.89314	0.0000000		
AR								
RNDLR	0.493004	0.0000000			−0.624013	0.0000000	−0.079591	0.0185440
SALESLR	−0.066841	0.0000000			0.05663	0.0000000		
RNDLE	−0.119173	0.0617930			−0.127605	0.0000000		
SALESLE	0.025982	0.0128650			0.049539	0.0000000		

Abbreviations: CV (Cardiovascular), CNS (Central Nervous System), Derma (Dermatology), EMGD (Endocrine, Metabolic and Genetic Disorders), GIM (Gastroenterology), GU (Genitourinary disorder), Hema (Hematology), InI (Immunology and Inflammation), Musk (Musculoskeletal), Onco (Oncology), Resp (Respiratory).

Table 6. Results of regression analysis of deal value by drug class (2).

Drug Class	GIM		GU		InI		Onco		Resp	
***p*-value (Model)**	0.0000000		0.0115290		0.0002610		0.0000000		0.0000000	
# of sample	**26**		**16**		**38**		**290**		**30**	
Statistical coeff.	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**
Constant	71.8946	0.10576	207.2958	0.0236750	190.44		230.7344	0.0003370	80.8933	0.0001190
Indep, Var.										
PDELR	9.9896	0.00150					7.877775	0.0000000	−3.0855	0.0000020
PDELE									9.26248	0.0000010
AR							−2.758797	0.0454660		
RNDLR	−0.7448	0.00000			0.1505	0.0002	0.267436	0.0000670	0.17422	0.0000000
SALESLR	0.1276	0.00000	0.01447	0.0055300			−0.038537	0.0000560	−0.01611	0.0000000
RNDLE			−22.9687	0.0212000	0.1098	0.0047	0.341313	0.0000410	0.21402	0.0000000
SALESLE							−0.04113	0.0028330		

5.3. Regression Analysis of Royalty Rate by Drug Class

In a similar way with the afore-mentioned cases for "influencing factors-deal value" relationships, we performed the regression analysis on royalty rate (dependent variable) by drug class in Tables 7 and 8 and obtained the algebraic relationships between each independent variable and royalty rate.

Table 7. Results of regression analysis of royalty rate average by drug class (1).

Drug Class	CV		CNS		Derma		EMGD	
***p*-value (Model)**	0.0002690		0.0066530		0.0000000		0.0015070	
# of sample	**15**		**55**		**16**		**21**	
Statistical coeff.	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**
Constant	10.281316	0.0001140	9.510447	0.0000010	9.312754	0.0000000	9.833102	0.0289490
Indep, Var.								
PDELR	−0.366691	0.0405490	0.085097	0.0115640			−0.354185	0.0033750
PDELE								
AR			0.060733	0.0479160			0.201261	0.0026940
RNDLR					0.037056	0.0000000		
SALESLR	0.001478	0.0027060					0.000622	0.0439070
RNDLE							−0.006678	0.0339430
SALESLE							0.001063	0.0495990

Table 8. Results of regression analysis of average royalty rate by drug class (2).

Drug Class	GIM		InI		Onco		Resp	
***p*-value (Model)**	0.0000000		0.0026550		0.0233130		0.0000000	
# of sample	**14**		**16**		**164**		**22**	
Statistical coeff.	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**
Constant	4.153846	0.0000000	7.913783	0.0000000	9.668651	0.0000000	11.78705	0.0000000
Indep, Var.								
PDELR	0.153846	0.0000000					−0.11326	0.0000230
PDELE	−11.269231	0.0000000						
AR					0.06947	0.0233130	−0.042263	0.0130290
RNDLR			0.002781	0.0026550			−0.004541	0.0000060
SALESLR							0.000842	0.0000000
RNDLE								
SALESLE	2.044872	0.0000000					0.000416	0.0000040

The formula to predict the average royalty rate by drug class is as follows.

(1) CV

$$\text{Royalty Rate} = 10.281316 - 0.366691 \times \text{Previous Licensor Deal experience} + 0.001478 \times \text{Licensor Sales} \quad (14)$$

(2) CNS

$$\text{Royalty Rate} = 9.510447 + 0.085097 \times \text{Previous Licensor Deal experience} + 0.060733 \times \text{Attrition Rate} \quad (15)$$

(3) Derma

$$\text{Royalty Rate} = 9.312754 + 0.037056 \times \text{Licensor R\&D Costs} \quad (16)$$

(4) EMGD

$$\text{Royalty Rate} = 9.833102 - 0.354185 \times \text{Previous Licensor Deal experience} + 0.201261 \times \text{Attrition Rate} + 0.000622 \times \text{Licensor Sales} - 0.006678 \times \text{Licensee R\&D Costs} + 0.001063 \times \text{Licensee Sales} \quad (17)$$

(5) GIM

$$\text{Royalty Rate} = 4.153846 + 0.153846 \times \text{Previous Licensor Deal experience} - 11.269231 \times \text{Previous Licensee Deal Experience} + 0.744804 \times \text{Licensor R\&D Costs} + 2.044872 \times \text{Licensor Sales} \quad (18)$$

(6) GU

There were two samples in the Genitourinary disorder dataset, which was too small to perform the regression analysis.

(7) Hema

There were four samples in the Haematology disorder dataset, which was too small to perform the regression analysis.

(8) InI

$$\text{Royalty Rate} = 7.913783 + 0.002781 \times \text{Licensor R\&D Costs} \quad (19)$$

(9) Musk

There were two samples in the Musculoskeletal dataset, which was too small to perform the regression analysis.

(10) Onco

$$\text{Royalty Rate} = 9.668651 + 0.06947 \times \text{Attrition rate} \quad (20)$$

(11) Resp

$$\text{Royalty Rate} = 11.78705 - 0.11326 \times \text{Previous Licensor Deal experience} - 0.042263 \times \text{Attrition Rate} - 0.004541 \times \text{Licensor R\&D Costs} + 0.000842 \times \text{Licensor Sales} + 0.000416 \times \text{Licensee Sales} \quad (21)$$

5.4. Regression Analysis of Total Upfront Payment by Drug Class

Here, we got to the regression analysis on Total Upfront (TU) payment (dependent variable) by drug class in Tables 9 and 10, and obtained the algebraic relationships between each independent variable and TU.

Table 9. Results of regression analysis of total upfront payment by drug class (1).

Drug Class	**CV**		**CNS**		**EMGD**		**GIM**	
***p*-value (Model)**	0.0000000		0.0000000		0.0129930		0.0000000	
# of sample	**13**		**67**		**31**		**22**	
Statistical coeff.	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**
Constant	−17.315041	0.0000220	14.924031	0.1652240	201.386616	0.0009260	37.502781	0.0000000
Indep, Var.								
PDELR	0.996379	0.0000150	0.603123	0.0372910	3.248232	0.0219400		
PDELE	2.645786	0.0000000	2.675739	0.0000000			−0.945875	0.0044590
AR	−0.07082	0.0364460			−2.09025	0.0113520		
RNDLR	0.09439	0.0001490	0.048442	0.0033510	−0.060985	0.0027910	−0.126786	0.0000000
SALESLR	−0.016922	0.0000400	−0.007446	0.0017110			0.021347	0.0000020
RNDLE							−0.278727	0.0000000
SALESLE					−0.006299	0.0349960	0.043333	0.0000000

Table 10. Results of regression analysis of total upfront payment by drug class (2).

Drug Class	**GU**		**InI**		**Onco**		**Resp**	
***p*-value (Model)**	0.0000000		0.0003120		0.0000000		0.0000000	
# of sample	**12**		**26**		**228**		**28**	
Statistical coeff.	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**
Constant	−13.781255	0.3798700	19.251567	0.2268740	73.656498	0.0000000	37.02934	0.0000000
Indep, Var.								
PDELR	0.740959	0.0258880	−1.644673	0.0127100	0.619589	0.0096870	−0.460522	0.0012580
PDELE	8.925765	0.0017840			−1.309108	0.0055380	1.473402	0.0005760
AR					−0.539162	0.0335760		
RNDLR			0.045357	0.0052920			0.032099	0.0000000
SALESLR					−0.001444	0.0054320	−0.003834	0.0000000
RNDLE			0.151248	0.0000190	0.124938	0.0000000		
SALESLE			−0.018931	0.0000870	−0.016661	0.0000000		

The formula to predict total upfront payment by drug class is as follows.

(1) CV

$$\text{Total Upfront Payment} = (-17.315041) + 0.996379 \times \text{Previous Licensor Deal experience} + 2.645786 \times \text{Previous Licensee Deal experience} - 0.07082 \times \text{Attrition Rate} + 0.09439 \times \text{Licensor R\&D Costs} - 0.016922 \times \text{Licensor Sales} \quad (22)$$

(2) CNS

$$\text{Total Upfront Payment} = 14.924031 + 0.603123 \times \text{Previous Licensor Deal experience} + 2.675739 \times \text{Previous Licensee Deal experience} + 0.048442 \times \text{Licensor R\&D Costs} - 0.007446 \times \text{Licensor Sales} \quad (23)$$

(3) Derma

There were five samples in the Dermatology dataset, which was too small to perform the regression analysis.

(4) EMGD

$$\text{Total Upfront Payment} = 201.386616 + 3.248232 \times \text{Previous Licensor Deal experience} - 2.09025 \times \text{Attrition Rate} - 0.060985 \times \text{Licensor R\&D Costs} - 0.006299 \times \text{Licensee Sales} \quad (24)$$

(5) GIM

$$\text{Total Upfront Payment} = 37.502781 - 0.945875 \times \text{Previous Licensee Deal Experience} - 0.126786 \times \text{Licensor R\&D Costs} + 0.021347 \times \text{Licensor Sales} - 0.278727 \times \text{Licensee R\&D Costs} + 0.043333 \times \text{Licensee Sales} \quad (25)$$

(6) GU

$$\text{Total Upfront Payment} = (-13.781255) + 0.740959 \times \text{Previous Licensor Deal Experience} + 8.925765 \times \text{Previous Licensee Deal Experience} \quad (26)$$

(7) Hema

There were four samples in the Haematology dataset, which was too small to perform the regression analysis.

(8) InI

$$\text{Total Upfront Payment} = 19.251567 - 1.644673 \times \text{Previous Licensor Deal Experience} + 0.045357 \times \text{Licensor R\&D Costs} + 0.151248 \times \text{Licensee R\&D Costs} - 0.018931 \times \text{Licensee Sales} \quad (27)$$

(9) Musk

There were five samples in the Musculoskeletal dataset, which was too small to perform the regression analysis.

(10) Onco

$$\text{Total Upfront Payment} = 73.656498 + 0.619589 \times \text{Previous Licensor Deal Experience} - 1.309108 \times \text{Previous Licensee Deal Experience} - 0.539162 \times \text{Attrition rate} - 0.001444 \times \text{Licensor Sales} + 0.124938 \times \text{Licensee R\&D Costs} - 0.016661 \times \text{Licensee Sales} \quad (28)$$

(11) Resp

$$\text{Total Upfront Payment} = 37.02934 - 0.460522 \times \text{Previous Licensor Deal experience} + 1.473402 \times \text{Previous Licensee Deal Experience} + 0.032099 \times \text{Licensor R\&D Costs} - 0.003834 \times \text{Licensor Sales} \quad (29)$$

5.5. Regression Analysis of Milestone Payment by Drug Class

Lastly, we performed the regression analysis on Milestone Payment (dependent variable) by drug class in Tables 11 and 12 and obtained the algebraic models for MP.

Table 11. Results of regression analysis of milestone payment by drug class (1).

Drug Class	**CV**		**CNS**		**EMGD**		**GU**	
***p*-value (Model)**	0.0000000		0.0000090		0.0607760		0.0000000	
# of sample	**10**		**57**		**18**		**12**	
Statistical coeff.	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**
Constant	36.294468	0.0000000	46.138492	0.1486550	344.2195	0.0000220	−402.833	0.0000000
Indep, Var.								
PDELR			2.421873	0.0001520			19.747326	0.0000000
PDELE	5.658716	0.0000000	3.827295	0.0002150			144.32640	0.0000000
AR								
RNDLR	0.444609	0.0000000					0.53252	0.0000000
SALESLR	−0.067315	0.0000000					−0.081658	0.0000000
RNDLE					−4.214859	0.0607760	646.4750	0.0000000
SALESLE								

Table 12. Results of regression analysis of milestone payment by drug class (2).

Drug Class	**InI**		**Onco**		**Resp**	
***p*-value (Model)**	0.0035970		0.0000000		0.0000000	
# of sample	**26**		**174**		**17**	
Statistical coeff.	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**
Constant	281.395629	0.0021770	121.1235	0.0210360	789.470761	0.0000000
Indep, Var.						
PDELR			14.947359	0.0000000	−14.399465	0.0000000
PDELE					−6.724867	0.0000000
AR						
RNDLR			0.507199	0.0000000		
SALESLR	0.016733	0.0035970	−0.081482	0.0000000		
RNDLE						
SALESLE						

The formula to predict the millstone payment by drug class is as follows.

(1) CV

$$\text{Milestone Payment} = 36.294468 + 5.658716 \times \text{Previous Licensee Deal experience} + 0.444609 \times \text{Licensor R\&D Costs} - 0.067315 \times \text{Licensor Sales} \quad (30)$$

(2) CNS

$$\text{Milestone Payment} = 46.138492 + 2.421873 \times \text{Previous Licensor Deal experience} + 3.827295 \times \text{Previous Licensee Deal experience} \quad (31)$$

(3) Derma

There were two samples in the Dermatology dataset, which was too small to perform the regression analysis.

(4) EMGD

$$\text{Milestone Payment} = 344.219519 - 4.214859 \times \text{Licensee R\&D Costs} \quad (32)$$

(5) GIM

There were eight samples in the Gastroenterology dataset, which was too small to perform the regression analysis.

(6) GU

$$\begin{gathered}\text{Milestone Payment} = (-402.833709) + 19.747326 \times \text{Previous Licensor Deal} \\ \text{Experience} + 144.326402 \times \text{Previous Licensee Deal Experience} + 0.53252 \times \text{Licensor} \\ \text{R\&D Costs} - 0.081658 \times \text{Licensor Sales} + 646.475074 \times \text{Licensee R\&D Costs}\end{gathered} \quad (33)$$

(7) Hema

There was one sample in the Haematology dataset, which was too small to perform the regression analysis.

(8) InI

$$\text{Milestone Payment} = 281.395629 + 0.016733 \times \text{Licensor Sales} \quad (34)$$

(9) Musk

There were four samples in the Musculoskeletal dataset, which was too small to perform the regression analysis.

(10) Onco

$$\begin{gathered}\text{Milestone Payment} = 121.123558 + 14.947359 \times \text{Previous Licensor Deal Experience} \\ + 0.507199 \times \text{Licensor R\&D Costs} - 0.081482 \times \text{Licensor Sales}\end{gathered} \quad (35)$$

(11) Resp

$$\begin{gathered}\text{Milestone Payment} = 789.470761 - 14.399465 \times \text{Previous Licensor Deal Experience} \\ - 6.724867 \times \text{Prior Licensee Deal Experience}\end{gathered} \quad (36)$$

6. Discussion and Conclusions

In this study, we have investigated influencing factors directly coupled with pricing in patent licensing contracts in the biopharmaceutical industry based on a dataset that includes royalty-related data such as running royalty rate, up-front payment, milestones, and deal value. We have also considered multiple input descriptors such as market factors, licensor factors, and licensee factor, assuming that royalty-related data could be statistically treated or analyzed by drug class in order to derive the formula for predicting various types of royalty-related deal value estimates.

Depending on the drug class, most of the factors related to the amount of technology transactions such as the costs for the clinical phases, the attrition rate, the drug development time, the average sales amount, and the sales curve, and control over pricing by country-specific regulators change [12,59]. Cardiovascular disease drugs have a higher probability of entering the market than oncology drugs, and the clinical success rate of protein therapeutics is higher than that of chemical drugs [59]. Real price statistics show that the real price for eye therapeutic class is the lowest (USD 90.87) and the real price for viral infections is highest (USD 637.69) [60]. However, existing valuation methodologies, such as r-NPV, do not take into account factors that vary depending on the drug class. The afore-mentioned valuation methodologies would only consider successful probability and investment cost at each pre-clinical/clinical stage as well as typical principal variables such as technology economic life, cash flow estimation, discount rates, technology factor (or contribution rate). Here, successful probability and investment cost are not related nor sensitive to drug class yet. For this reason, a regression study that can reveal these variables that can be changed according to the drug class is meaningful. If the expected development cost of drugs is relatively low and the expected operating

profit is relatively high, the drug is of course profitable. An example is the orphan drug, a drug for rare diseases. The market size of orphan drug is lower than that of general medicine, but the cost of medicine per patient is much higher than the average cost of general medicine. Orphan drugs are eligible for special tax deductions and other benefits [59]. For this reason, we have reached the possible hypothesis that some of the variables used in the regression analysis according to the drug class may work properly, and some variables may not, leading to the fact that we might find significant variables with corresponding coefficients from the regression analysis. In previous similar studies, we have derived a formula that predicts the royalties and upfront payment through regression analysis for anticancer and cardiovascular drug classes [1]. In this study, the formula type of the regression model for the oncology drug was "Rational Model, 3 Parameter Type 2 Regression" and the formula type of the regression model for the cardiovascular drug was the "Polynomial Model, Inverse Second Order-type Regression". Curve types for oncology drugs and cardiovascular drugs were also different [1].

While taking the integration of regression analysis results in preceding sub-sections in Section 5, we find that most regression models involve two or more independent variables in either (+) or (−) proportionality relations, except for several cases such as Royalty Rate for Derma, InI, Onco and Milestone Payment for EMGO, InI.

The proportional relationship between dependent and independent variables in the regression analysis on factors affecting pricing in patent licensing contracts in the biotech industry are illustrated in detail in Table 13. Technical fees such as DV, MP are in directly proportional to PDELR, CAGR, RNDLR, and SALESLE while DV is inversely proportional to AR. DV and MP is inversely proportional to SALESLR, but TU is directly proportional to SALESLR. Factors that influence all technical fees including deal value, royalty rate, upfront payment and milestones are ranked as follows: ① CAGR, ② PDELR, ③ AR, ④ RNDLR, ⑤ RNDLE, ⑥ SALESLR, ⑦ SALESLE. MS and PDELE are excluded in the factors affecting pricing in patent licensing contracts, because p-value for MS and PDELE was statistically not meaningful in the regression result. Although the market size for the sub-classical drug class can be used for regression to obtain more accurate results, it is difficult to obtain market size information corresponding to the subclassification. The market size used for the actual regression is 11 drug classes corresponding to the major category. For this reason, we assume the p-value for MS is not statistically significant. We need further study why MS and PDELE are excluded in the factors affecting pricing in patent licensing contracts. We found that three most important variables to consider in the licensing deal in biotech industry are CAGR, PDELR, and AR. Knowing the factors to consider in the licensing deal is very important to prepare for the licensing deal negotiation and it is advantageous to have a better positioning in the negotiation.

In Table 13, we find that statistically CAGR has a positive influence on DV and MP, but it has no relations with RRA and TU. This implies that RRA and TU can be influenced by licensee's financial status and company circumstances. In the meanwhile, DV and MP might be enhanced in accordance with economic growth and relevant factors such as a firm's technical necessity and willingness-to-pay, etc.

Table 13. Proportional relationship in the regression analysis.

	DV	RRA	MP	TU
PDELR	+		+	+
CAGR	+		+	
AR	−			
RNDLR	+		+	+
SALESLR	−		−	+
RNDLE	+	−		
SALESLE		+		

+: Dependent variables are directly proportional to independent variables, −: Dependent variables are inversely proportional to independent variables.

The proportional relationship between dependent and independent variables by drug class in the regression analysis on factors affecting pricing in patent licensing contracts in biotech industry are illustrated in detail in Tables 14–16. The total frequency of factors in the formula to estimate all technical fees including deal value, royalty rate, upfront payment, and milestones by drug class is as follows: ① PDELR (22), ② RNDLR (16), ③ PDELE (15), ④ SALESLE, SALESLR (14), ⑤ AR (9). We found that the three most important factors in the frequency in the formula to estimate the license fee are PDELR, RNDLR and PDELE. Factors that influence all technical fees including deal value, royalty rate, upfront payment and milestones are ranked from the viewpoint of B as follows: ① PDELE, ② PDELR, ③ AR, ④ RNDLR, ⑤ RNDLE, ⑥ SALESLR, ⑦ SALESLE. In most cases technical fees are directly proportional to PDELE, PDELR, RNDLR, and SALESLE while inversely proportional to SALESLR. It is interesting that factors in the formula to estimate the technical fee are totally different by drug class.

Table 14. Proportional relationship in the regression analysis by drug class (1)

Drug Class	**CV**				**CNS**				**Derma**				**Freq.**
Indep Var.	**DV**	**RRA**	**TU**	**MP**	**DV**	**RRA**	**TU**	**MP**	**DV**	**RRA**	**TU**	**MP**	
Dep Var.													
PDELR	−	−	+		+	+	+	+	+				**8**
PDELE	+		+	+	+		+	+	+				**7**
AR			−			+			+				**3**
RNDLR	+		+	+			+			+			**5**
SALESLR		+	−	−			−						**4**
RNDLE													**0**
SALESLE	+												**1**

Table 15. Proportional relationship in the regression analysis by drug class (2).

Drug Class	**EMGD**				**GIM**				**GU**				**Freq.**
Indep Var.	**DV**	**RRA**	**TU**	**MP**	**DV**	**RRA**	**TU**	**MP**	**DV**	**RRA**	**TU**	**MP**	
Dep Var.													
PDELR	+	−	+		+	+				+	+		**7**
PDELE						−	−			+	+		**4**
AR		+	−										**2**
RNDLR	−		−		−		−						**4**
SALESLR	+	+			+		+		+				**5**
RNDLE		−		−		+	−		−		+		**6**
SALESLE			−				+						**2**

Table 16. Proportional relationship in the regression analysis by drug class (3).

Drug Class	**CV**				**CNS**				**Derma**				**Freq.**
Indep Var.	**DV**	**RRA**	**TU**	**MP**	**DV**	**RRA**	**TU**	**MP**	**DV**	**RRA**	**TU**	**MP**	
Dep Var.													
PDELR			−		+		+		−	−	−	−	**7**
PDELE							−		+		+	−	**4**
AR					−			+		−			**3**
RNDLR	+		+		+	+			+	−	+		**7**
SALESLR	−				−				−	+	−		**5**
RNDLE	+	+	+		+		+	+	+				**7**
SALESLE			−	+			−	−		+			**5**

We can see from the above that factors in the formula to estimate the license fee are totally different by drug class. This study is meaningful in that it is the first one to suggest a method of estimating four types of technical fee for most of drug classes.

Usually the DCF method often results in a negative value when applied to early-stage drugs [1]. In fact, when evaluating the economic value of a technology or business project including biotechnology

fields, we need to consider the period and cost for commercialization due to pre-clinical/clinical demonstration. Since the discounted cash flow (DCF) method has limitations in that it cannot consider consecutive investments or does not reflect the probabilistic property of commercialization cost, we often take it desirable to apply the concept of 'Real Option' with key metrics of underlying asset value, commercialization cost, and volatility, while regarding the value of technology and investment as the opportunity value [61]. More elaborated real options model, which reflects the uncertainty in the option pricing model (OPM), can provide a feasible solution to overcome the challenges of rNPV, widely used in biotechnology or pharmaceutical industries. Therefore, the Real Option method often has advantages over the DCF method in that it has the flexibility to cope with changes in the external environment but has often been criticized for offering too high a valuation price. Estimating future product sales by the Real Option method is very difficult due to market changes due to fierce competition, the emergence of new science and technology, and possible additional indication [59]. rNPV is an effective tool to approximate value in late stage products with well-defined markets, but the predictive power of rNPV method is heavily dependent on accurate estimates of multiple factors like market size, market share, project costs, project timing, probabilities of success at each major milestone and discount rate. However, it is not easy and one to require a lot of time to estimate multiple variables accurately. Overall, valuation of drug candidates for licensing remains more art than science. Objective valuation methods exist but require a lot of subjective inputs to generate estimates of value [62]. On the other hand, the method presented in this study can be used to estimate the license fee as an input of objective data that can be easily obtained, and it is also applicable to early-stage drugs as well as late stage drugs. The valuation is essential in finding licensing partner, fundraising for further development, portfolio management in biotech industry [12] and the result of regression for 11 drug classes can be a good starting point to be referred to by a manager in case of negotiations in biotech licensing deals (for finding licensing partner and fundraising) for a specific drug classification. The result can be a good starting point to manage the portfolio within biotech company. The regression models of this study could be used for the following purposes: (1) Derive the base amount that will be the starting point of the negotiations for drug licensing tasks in Biotech and in-License/Out-License departments of biotech and pharmaceutical companies (2) Assist decision-making of go/no-go of a specific project among multiple drug pipelines. (3) Pre-economic evaluation of national research project related to medicine. Technology licensing, M&A, and partnership are main open innovation strategies on the closed innovation system [59]. So, the results of this study are expected to be helpful tools for implementing open innovation strategies. Since the Fourth Industrial Revolution affects business models, it could reshape the organizational forms to deliver values also [63]. So, the results of this study are expected to be helpful to reshape the organizational forms to deliver better value in the Fourth Industrial Revolution age. Further in-depth research is necessary for the following topics in the future: (1) Regression analysis using more independent variables like technical life cycle, number of patented countries, quality of technology and so on. (2) Case study comparing the regression model in this study with DCF and rNPV method.

Author Contributions: J.H.L. primarily conducted research. T.-E.S. and E.K. participated in the design of the research and helped to draft the manuscript. E.K. and T.-E.S. helped to carry out a systematic literature review and T.-E.S. and E.K. helped to derive the implication from the regression analysis. K.S. conceived of the research and participated in its design and coordination. All authors read and approved the final manuscript.

Funding: This research is also supported by The International Science and Business Belt Program through the Ministry of Science, ICT and Future Planning (2016K000282), Republic of Korea., by the Medical Research Information Center of the National Research Foundation through the Ministry of Science and ICT (2018R1A6A6040880), Republic of Korea, and financially supported by Korea Institute of Science and Technology Information (KISTI) on the academic (commissioned) research program of "Research on analysis indicators utilizing corporate big data" of 2018 (2018-P18051).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Lee, J.H.; In, Y.; Lee, I.; Lee, J.W. Valuations using royalty data in the life sciences area—Focused on anticancer and cardiovascular therapies. *J. Open Innov. Technol. Mark. Complex.* **2016**, *2*, 1–25. [CrossRef]
2. Yourgenome. How Are Drugs Designed and Developed? Available online: https://www.yourgenome.org/facts/how-are-drugs-designed-and-developed (accessed on 26 April 2018).
3. Young, P.; Biotech Financial and M&A Trends-two steps forward, one step back. *Pharm. Executive* 2016. Available online: http://www.pharmexec.com/biotech-financial-and-ma-trends-two-steps-forward-one-step-back (accessed on 5 March 2018).
4. Deloitte Centre for Health Solutions. Global Life Sciences Outlook: Adapting in an Era of Transformation. 2015. Available online: https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Life-Sciences-Health-Care/gx-lshc-2015-lifesciences-report.pdf (accessed on 5 March 2018).
5. Mergermarket. Global Technology, Media & Telecommunications Trend Report. 2014. Available online: https://qz.com/244435/whats-really-going-on-with-all-those-crazy-tech-deals-in-charts/ (accessed on 22 April 2018).
6. Nigel Borshell, N.; Ahmed, T. Approaches to Valuation of Pharmaceutical Licensing Deals. Pharma Ventures. 2012. Available online: http://files.pharmadeals.net/contents/Sample_Valuation.pdf (accessed on 1 March 2018).
7. Lee, S.; Lee, K. Heterogeneous expectations leading to bubbles and crashes in asset markets: Tipping point, herding behavior and group effect in an agent-based model. *J. Open Innov. Technol. Mark. Complex.* **2015**, *1*, 12. [CrossRef]
8. Lee, J.H.; Bae, K.S.; Lee, J.W.; In, Y.; Kwon, T. Valuation method by regression analysis on real royalty-related data by using multiple input descriptors in royalty negotiations in life science area-focused on anticancer therapies. *J. Open Innov. Technol. Mark. Complex.* **2016**, *2*, 1–22. [CrossRef]
9. Thomas, D.W.; Burns, J.; Audette, J.; Carroll, A.; Dow-Hygelund, C.; Hay, M. Clinical Development Success Rates 2006–2015. BIO Industry Analysis, Biotechnology Innovation Organization (BIO). 2016. Available online: https://www.bio.org/sites/default/files/Clinical%20Development%20Success%20Rates%202006-2015%20-%20BIO,%20Biomedtracker,%20Amplion%202016.pdf (accessed on 2 January 2018).
10. Paik, S. Identification of factors affecting technology licensing via expert survey. *J. Korea Technol. Innov. Soc.* **2008**, *11*, 476–509.
11. Sakakibara, M. An empirical analysis of pricing in patent licensing contracts. *Ind. Corp. Chang.* **2010**, *19*, 927–945. [CrossRef]
12. Bogdan, B.; Villiger, R. *Valuation in Life Sciences: A Practical Guide*, 3rd ed.; Springer: New York, NY, USA, 2010.
13. Patra, S.K.; Krishna, V.V. Globalization of R&D and open innovation: Linkages of foreign R&D centers in India. *J. Open Innov. Technol. Mark. Complex.* **2015**, *1*, 1–24.
14. Nguyen, X.; Sgro, P.; Nabin, M. Optimal Licensing Policy under Vertical Product Differentiation. *Rev. Dev. Econ.* **2017**, *21*, 497–510. [CrossRef]
15. Ruckman, K.; McCarthy, I. Why do some patents get licensed while others do not? *Ind. Corp. Chang.* **2016**, *29*, 1–22. [CrossRef]
16. Hwhang, H.D.; Chung, S.Y. A Measure on Technology Transfer Activation of Government-Sponsored Research Institutes Focusing on Companies in Demand: Focusing on the Cases in the K Research Institute. *J. Korea Technol. Innov. Soc.* **2015**, *18*, 318–337.
17. Anand, B.N.; Khanna, T. The Structure of Licensing Contracts. *J. Ind. Econ.* **2000**, *48*, 103–135. [CrossRef]
18. Fosfuri, A. The licensing dilemma: Understanding the determinants of the rate of technology licensing. *Strateg. Manag. J.* **2006**, *27*, 1141–1158. [CrossRef]
19. Rivette, K.G.; Kline, D. *Rembrandt in the Attic: Unlocking the Hidden Value of Patents*; Harvard Business School Press: Cambridge, MA, USA, 2000.
20. Schankerman, M. How valuable is patent protection? Estimates by technology field. *RAND J. Econ.* **1998**, *29*, 77–107. [CrossRef]
21. Griliches, Z. Market value, R&D and patents. *Econ. Lett.* **1981**, *7*, 183–187.
22. Lanjouw, J.O. Patent protection in the shadow of infringement: Simulation estimations of patent value. *Rev. Econ. Stud.* **1998**, *65*, 671–710. [CrossRef]

23. Harhoff, D.; Scherer, F.M.; Vopel, K. Citations, family size, opposition and the value of patent rights. *Res. Policy* **2003**, *32*, 1343–1363. [CrossRef]
24. Gambardella, A.; Harhoff, D.; Verspagen, B. The value of European patents. *Eur. Manag. Rev.* **2008**, *5*, 69–84. [CrossRef]
25. Bessy, C.; Brousseau, E. Technology licensing contracts: Features and diversity. *Int. Rev. Law Econ.* **1998**, *18*, 451–489. [CrossRef]
26. Sampat, B.N.; Ziedonis, A.A. *Cite Seeing: Patent Citations and the Economic Value of Patents*; Working Paper; University of Michigan: Ann Arbor, MI, USA, 2002.
27. Shane, S. Selling university technology: Patterns from MIT. *Manag. Sci.* **2002**, *48*, 122–137. [CrossRef]
28. Caviggioli, F.; Ughetto, E. The drivers of patent transactions: Corporate views on the market for patents. *R&D Manag.* **2013**, *43*, 318–332.
29. Falk, N.; Train, K. Patent Valuation with Forecasts of Forward Citations. *J. Bus. Valuat. Econ. Loss Anal.* **2017**, *12*, 101–121. [CrossRef]
30. DiMasi, J.A.; Feldman, L.; Seckler, A.; Wilson, A. Trends in risks associated with new drug development: Success rates for investigational drugs. *Clin. Pharmacol. Ther.* **2010**, *87*, 272–277. [CrossRef] [PubMed]
31. Byun, J.W.; Lee, S.C.; Huh, N.I. A study on the effects of negotiation technique on the terms and conditions of technology transaction agreement. *Korean Corp. Manag. Rev.* **2013**, *20*, 215–232.
32. Baek, J.; Hyun, B. A study on the determinant priority of royalty between government-funded research centers and companies who were transferred the technology; focused on the case of 'N' center. *J. Korea Acad.-Ind. Coop. Soc.* **2017**, *18*, 135–145.
33. Baek, J.; Hyun, B. A comparative study on the determinants priority of the royalty in national R&D project—Focused on the case of 'N' center's technology transfer. *J. Korea Technol. Innov. Soc.* **2017**, *20*, 430–457.
34. Yun, D.; Park, I.; Yoon, B. Development of a technology valuation method for buyers in technology transfer. *J. Korea Acad.-Ind. Coop. Soc.* **2016**, *17*, 155–167. [CrossRef]
35. Zaharoff, H. Setting values and royalty rates for medical and life science businesses. *J. Biolaw Bus.* **2004**, *7*, 7–9.
36. Oong Hyun, S. Preliminary Study on Royalty Decision Model in Biotechnology.
37. Park, H.W. Structure and Determinants of Royalty in Pharmaceutical Licensing. *J. Korea Technol. Innov. Soc.* **2007**, *10*, 406–430.
38. Park, S.M.; Park, I.S. Effects of prior experience and the number of project on individual-Level technology commercialization. *J. Technol. Innov.* **2013**, *21*, 95–119.
39. Kwon, K.W. Activation of IP and technology trading market as a medium of open innovation. *Sci. Technol. Policy* **2015**, *25*, 36–45.
40. Hong, S.I.; Kim, J.S.; Kim, J.H. A Study on Antecedents and Performance of Technology Transfer from Overseas R&D Center. In Proceedings of the KIIE (Korean Institute of Industrial Engineers), Spring Conference, Kyungsung University, Pusan, Kore, 1998; pp. 725–733.
41. Svačina, P. An empirical analysis of factors affecting prices of intangible assets: A preliminary testing in consumer durables sector. *Prague Econ. Papers* **2015**, *24*, 354–363. [CrossRef]
42. Global View Research. *Central Nervous System (CNS) Therapeutic Market Analysis by Disease (Neurovascular, Trauma, Mental Health, Degenerative Disorder [Alzheimer's Disease, Parkinson's Disease, Multiple Sclerosis], Infections, Cancer), & Segment Forecasts, 2018–2025*; Global View Research: San Francisco, CA, USA, July 2017.
43. Evaluate Pharma. *World Preview 2017, Outlook to 2022*, 10th ed. Available online: Availableonline:http://info.evaluategroup.com/rs/607-YGS-364/images/WP17.pdf (accessed on 2 September 2018).
44. Transparency Market Research. *Gastrointestinal Drugs Market—Global Industry Analysis, Size, Share, Growth, Trends, and Forecast 2016–2024*; Transparency Market Research: Albany, NY, USA, March 2017.
45. Grand View Research. *Genitourinary Drugs Market by Indication (Prostate, Ovarian, Bladder, Cervical Cancer, Erectile Dysfunction, UTI, Urinary Incontinence & STD) by Product (Urologicals, Hormonal Therapy Drugs, Gynecological, Anti-infectives) and Segment Forecasts, 2018–2024*; Global View Research: San Francisco, CA, USA, November 2016.
46. Industry ARC. *Musculoskeletal Diseases Market: By Type (Rheumatoid Arthritis, Osteoarthritis, Osteoporosis, Psoriatic Arthritis, others); By Treatment (Biologics, Bmps, Composite Grafts, Others); By Musculoskeletal System (Tendons, Cartilage, Joints, Others); By Geography—Forecast (2018–2023)*; Industry ARC: Hyderabad, India, May 2018.

47. Garcia, A. *A Glimpse at the Global Blood Disease Market*. Born2Invest. Available online: https://born2invest.com/articles/glimpse-global-blood-disease-market/ (accessed on 2 September 2018).
48. Sung-Soo, S. A theroetical framework for the valuation of technoy. *J. Korea Technol. Innov. Soc.* **2000**, *3*, 5–21.
49. Bains, W.; Wooder, S. Funding biotech start-ups in a post-VC world. *J. Commercial Biotechnol.* **2014**, *20*, 10–27. [CrossRef]
50. Micklus, A.; Muntner, S. Biopharma deal-making in 2017. *Nat. Rev. Drug Discov.* **2018**, *17*, 91–92. [CrossRef] [PubMed]
51. Sung, T.; Kim, D.S.; Jang, J.; Park, H. An empirical analysis on determinant factors of patent valuation and technology transaction prices. *J. Korea Technol. Innov. Soc.* **2016**, *19*, 254–279.
52. Gallini, N.T.; Winter, R.A. Licensing in the theory of innovation. *RAND J. Econ.* **1985**, *16*, 237–252. [CrossRef]
53. Shepard, A. Licensing to enhance demand for new technology. *RAND J. Econ.* **1987**, *18*, 360–368. [CrossRef]
54. Kumar, S.; Luthra, S.; Abid Haleem, A.; Mangla, S.K.; Garg, D. Identification and evaluation of critical factors to technology transfer using AHP approach. *Int. Strateg. Manag. Rev.* **2015**, *3*, 24–42. [CrossRef]
55. Sung, O.H. Estimation method for reasonable running royalty rate based on classic 25% rule and royalty influential factors. *J. Korea Technol. Innov. Soc.* **2013**, *16*, 1090–11088.
56. Holmes, J.S., Jr. Societal and economic valuation of technology-transfer deals. *Acta Astron.* **2009**, *65*, 834–840. [CrossRef]
57. Sung, O.H. A study on the estimation of running royalty of biopharmaceutical technologies in licensing agreements. *Knowl. Manag. Rev.* **2010**, *11*, 37–50.
58. Yun, J.J. How do we conquer the growth limits of capitalism? Schumpeterian Dynamics of Open Innovation. *J. Open Innov. Technol. Mark. Complex.* **2015**, *1*, 17. [CrossRef]
59. Villiger, R.; Bogdan, B. Getting real about valuations in biotech. *Nat. Biotechnol.* **2005**, *23*, 423–428. [CrossRef] [PubMed]
60. Iacocca, K.; Sawhill, J.; Zha, Y. A multiple regression model to explain the cost of brand-drugs. *Socio-Econ. Plan. Sci.* **2013**, *47*, 238–246. [CrossRef]
61. Sung, T.; Park, H. The adequacy of volatility for the elaboration of technology valuation based on real options. *Technol. Anal. Strateg. Manag.* **2018**, 1–24. [CrossRef]
62. Hawkins, P.A. Regression Analysis of Oncology drug Licensing Deal Values. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA, USA, November 2006.
63. Lee, M.; Yun, J.J.; Pyka, A.; Won, D.; Kodama, F.; Schiuma, G.; Park, H.; Jeon, J.; Park, K.; Jung, K.; et al. How to Respond to the Fourth Industrial Revolution, or the Second Information Technology Revolution? Dynamic New Combinations between Technology, Market, and Society through Open Innovation. *J. Open Innov. Technol. Mark. Complex.* **2018**, *4*, 21. [CrossRef]

© 2018 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).