LICENSING IN PHARMA – VALUE CREATION AND APPROPRIATION

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CARL BECHT AND AXEL HASENKAMP

ABSTRACT

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Authors: Carl Becht (9405171811); Axel Hasenkamp (980123T219)

Advisor: Reda Moursli

Key Words: Pharma; Strategic Alliances; Licensing; Value Creation; Value Appropriation

Purpose: We unify literature on licensing in the pharmaceutical industry and empirically verify pre-established and identify new determinants of value creation and appropriation based on a contemporary data set of licensing deals made between 2015 and 2020.

Methodology: Short-Term Cumulative Abnormal Returns Event Study

Theoretical Perspectives: Bargaining Perspectives in Alliance Settings; Information Asymmetries and Contracting Design; Signaling Theory and Validation Effects

Empirical Foundation: Multiple Linear OLS Regression of Potential Determinants of Value Creation and Appropriation against Short-Term Cumulative Abnormal Returns

Conclusions: We observe positive returns for licensor and licensee. A return differential indicates value appropriation by the licensor due to scarcity. A positive validation effect occurs for both sides when the alliance partner is large. Aside from firm size, other firm-specific determinants hold little explanatory power. Contractual design considerations can have a significant impact on value creation and appropriation, most evidently when related to validation effects and issues of moral hazard. Determinants based on development phase and therapeutic area of the drug are not generalizable and require further research.

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1. INTRODUCTION

A growing body of empirical research has found that the productivity of research and development (R&D) is declining in a wide range of industries. This decline has been especially difficult for the pharmaceutical industry (Pammolli, 2011). Historically, pharmaceutical innovations have played an important role in improving public health and overall life expectancy. However, research and development concepts behind these successes are showing signs of fatigue as costs increase, innovation declines and competition intensifies (Munos, 2009). At the same time, the pharmaceutical industry is facing scrutiny from regulatory bodies due to aggressive price increases in the past decade (Banerjee and Siebert, 2017). Firms argue that rising prices are a consequence of increasing R&D costs (Banerjee and Siebert, 2017). Challenges facing the pharmaceutical industry are multifaceted and include increasing failure rates in development, increasing development times and changing regulatory requirements (Pushpakom et al., 2018).

Due to this change in the landscape of the pharmaceutical industry, there has been a growing number of alliances being formed between firms of all sizes (DiMasi et al., 2016) including most prominently licensing agreements (BIO, 2019). Licensing serves as a major source of financial resources for young, emerging, and innovative firms, while large, often multinational firms can expand and complement their internal research and development. While M&A activity in the pharmaceutical industry has ebbed, the market for drug licensing has noted rapid growth (BIO, 2019). The increasing popularity of strategic alliances is however not unique to the pharmaceutical industry. In fact, many CEOs of multinational firms from almost all industries claim to prioritize strategic alliances with other firms over M&A—strategic alliances are said to add capabilities that are crucially needed for operational success (KPMG, 2019). Studies show that entering research and development alliances often helps firms overcome innovation obstacles (Banerjee and Siebert, 2017).

Not just recently, strategic alliances have been subject to research—amongst others regarding their formation, governance, and performance (Gulati, 1998). Regarding their potential to generate economic value for the firms involved, one approach has been to explore the stock market's reaction to the announcement of such alliances, which is expected to proxy for changes in the firms' future performances (Higgins, 2007). Prior research on the relationship between alliance activities and shareholder value creation is ambiguous regarding its findings however (Bösecke, 2009). In addition, such empirical research specifically on licensing agreements is scarce (Walter, 2012). Given that licensing agreements are the most common type of strategic alliance in the pharmaceutical industry (Gassmann et al., 2016) and that innovation in this industry has undergone a dramatic shift in recent years (DiMasi et al., 2016), the research question of whether and how much value licensing creates for the parties involved is highly topical, both empirically and theoretically.

In addition to determinants of value creation themselves, the current research frontier also tries to answer how the created value is divided between the parties of the alliance (Adegbesan and Higgins, 2010)—so-called value appropriation. On one hand, this has given rise to a framework of so-called bargaining perspectives, which aim to explain the division of value based on superior asset complementarity, scarcity, and bargaining ability (Adegbesan, 2009; Lippman and Rumelt, 2003). On the other hand, there is also a growing body of research regarding contractual design in strategic alliances (Adegbesan and Higgins, 2010). A theory of optimal licensing contracts under information asymmetry has been developed specifically for the pharmaceutical industry (Crama et al., 2008; Dechenaux et al., 2009). Lastly, the validating role of the alliance partner has also been highlighted as a solution to mitigate information asymmetries based on signaling theory (Nicholson et al., 2005; Stuart et al., 1999).

Thus, we contribute to the research frontier by painting a contemporary picture of the licensing market and conciliating mayor strands of research regarding alliances and licensing in the pharmaceutical industry. We expand on existing considerations and empirical determinants of value creation and appropriation by introducing new variables, while verifying the significance of existing ones. We are able to render statistically and economically meaningful results, which on one hand add to the academic research frontier and on the other hand might also be of relevance for industry practitioners.

Conducting an event study of licensing deals, which were announced between 2015 and early-2020, and based on a proprietary data set obtained from *Bloomberg Intelligence*, we observe robust positive abnormal returns for both the licensor and licensee—4.41% and 0.76% respectively on average. These positive returns are consistent with previously observed abnormal returns in the strategic alliance literature (Chan et al., 1997; Das et al., 1998) as well as in the pharmaceutical-licensing literature (Anand and Khanna, 2000; Walter, 2012). The large return differential between licensor and licensee confines to the view that licensors are able to appropriate value from licensees due to their scarcity (Crama et al., 2008), as well as asymmetric dependency—in which small firms, thus often licensors, are generally able to appropriate a preponderance of the value created in an alliance setting (Das et al., 1998).

Abnormal returns are amplified whenever the alliance partner is large—a validation effect we find for both the licensor and licensee. In fact, small firms, which out-license to large firms, note 18.54% abnormal returns on average. A similar observation with 2.33% abnormal returns on average is made for small firms that in-license from large firms. Both observations support the mitigation of information asymmetries between small firms and their investors and future alliance partners due to a validation signal by a large, established firm. When controlling for the firm size of both parties, we find only weak support that other firm-specific characteristics are determinant of the ability to create or appropriate value from the alliance.

Our results furthermore suggest that contractual design considerations can have a significant impact on value creation and appropriation in alliance settings. For the licensor, the total value of the licensing deal, the transfer of global commercialization rights and the general transfer of commercialization rights to large alliance partners all show a statistically significant positive impact on returns. However, we find no evidence that licensors prefer upfront payments over conditional milestone payments, although they reflect direct cash infusions. For the licensee, the ratio of the upfront to milestone payments, surprisingly, is positively correlated with abnormal returns, at least for small and medium-sized firms. This is also inconsistent with predictions from theoretical literature, which state that licensees should prefer milestone over upfront payments as former mitigate risks of moral hazard by the licensor. Furthermore, we find support that R&D pledges, where the licensee pledges funds for research and development of the drug, increase moral hazard issues for the licensee.

Lastly, we find that relationships between information asymmetries related to characteristics of the underlying drug and value creation and appropriation are complex. Determinants appear to be vastly different for firms of different sizes on both sides of the licensing deal and inferences do not seem to be generalizable. We neither find support for information asymmetry-induced value creation and appropriation in oncology nor in the special research area of immuno-oncology. Regarding development phases, we find no evidence that drugs in the *Discovery* or *Preclinical Phase* generate information asymmetry-induced value creation either. However, licensing in *Phase III* appears to generate significant value for large licensees, while showing below-average returns for small- and medium-sized licensors, which hints at the presence of value appropriation mechanisms and a question of market expectations.

The remainder of our study is structured as follows. In Chapter 2, we provide the reader with necessary background information on the drug development process and licensing in the pharmaceutical industry. In Chapter 3, we illustrate the contemporary research frontier

regarding value creation and appropriation and related topics in the field of strategic alliances. In Chapter 4, we develop hypotheses partially based on a review of existing literature in the field and also derivations based on our theoretical framework. In Chapter 5, we illustrate how we create our sample data and discuss its ability to fairly represent the global population of licensing deals in the pharmaceutical industry. In Chapter 6, we derive our empirical methodology and show how we conduct our event study and how we specify regression models. Chapter 7 describes the results we create, and Chapter 8 concludes on our study and discusses further avenues of research.

2. BACKGROUND INFORMATION

This chapter is meant to introduce readers to the topic of licensing in the pharmaceutical industry. We start by describing the process a drug must undergo before it is commercialized, the topic of alliances and thus licensing in drug development and finally how licensing deals are valued. We conclude with an example of a licensing deal, which is meant to illustrate the intricacies of and possible motivations behind licensing in the pharmaceutical industry.

2.1 DRUG DEVELOPMENT

The development of drugs is a complex process, which has tended to become more complex and costlier over time. DiMasi et al. (2016) estimate the average total development cost of a new, market-ready drug to be USD 2,558 million worldwide. This corresponds to a 145% increase in costs compared to their previous study, which found costs to be USD 1,044 million on average (DiMasi et al., 2003). A major reason for these high development costs is the fact that development projects are more likely to fail than succeed, as there are significant attrition rates in each development phase (see Table 1).

Table 1: Global Attrition Rates in Drug Development

	Hay et al. (2014)	**Thomas et al. (2016)**	**Wong et al. (2018)**
Sample Size	4736	-	15102
Time Period	2003 - 2011	2006 - 2015	2000 - 2015
Phase I → *II*	35.50%	36.80%	61.20%
Phase II → *III*	67.60%	69.30%	61.80%
Phase I → Market	89.60%	90.40%	93.10%
Phase II → Market	83.80%	84.80%	88.80%
Phase III → Market	50.00%	50.40%	41.00%

Source: Hay et al. (2014); Thomas et al. (2016); Wong et al. (2018)

Gassmann et al. (2016) provide an overview of the different phases of drug development. Pharmaceutical research & development starts with the identification of a drug target that might play a role in treating a disease. In the next step, researchers attempt to identify so-called lead compounds, which then, if proving to be promising, can become drug candidates. These two steps are the so-called *Discovery Phase*. In the following *Preclinical Phase*, it is analyzed whether the drug candidate can be used in human trials. What follows are three so-called *Clinical Phases*. In *Phase I*, pharmacokinetics of the drug—how it affects bodily processes in humans—are investigated using a small group of human test subjects. In *Phase II*, safety and efficacy of the drug are tested on a group of patients that suffer from the targeted disease. In *Phase III*, the drug candidate is tested on a large set of patients to provide statistically useful data on safety and efficacy as well as its overall risk benefit ratio.

The drug development process has two important regulatory hurdles: (1) prior to clinical trials when an application for human testing is filed with regulatory agencies; and (2) at the end of clinical trials when an application for commercialization is filed (Arora et al., 2009).

In all stages of development, there is a significant possibility that the drug will not move forward—for example: 61.80% from *Phase II* to *Phase III* (Wong et al., 2018). It has been shown that this development risk has increased substantially over time (DiMasi et al., 2016). In fact, a recent study made by Wong et al. (2018) estimates that success rates in *Phase I* are significantly lower than previous studies indicate. Using the largest sample of pharmaceutical

compounds to date in combination with a comparably long time period from 2000 to 2015, Wong et al. (2018) conclude that the probability for a *Phase I*-drug to reach the market is 6.90%. Success rates are naturally lower when looking at drugs in the *Discovery* or *Preclinical Phase* (Paul et al., 2010). The probability of success also generally varies based on several other factors, such as the therapeutic area of the drug. The therapeutic area with the undoubtedly largest failure rate and thus highest development risk is oncology (Hay et al., 2014; Thomas et al., 2016; Wong et al., 2018).

Historically, the development of drugs was a fully integrated process in the pharmaceutical industry. However, over the last three decades, there has been continuous and substantial growth in the number and value of R&D alliances (Gassmann et al., 2018). R&D cooperation in early stages (i.e. *Discovery* or *Preclinical Phase*) serves to counter technology-, demand- and profit-uncertainties and to increase the likelihood of development success. Late-stage (i.e. *Clinical Phase*) R&D cooperation is less related to these uncertainties and more motivated by funding issues (Banerjee and Siebert, 2017).

One major reason for the increasing popularity of such alliances is the emergence of the biotechnology sector in the 1970's (Lerner et al., 2003).[1] As firms were then and are still today expected to create innovation at a constant pace, cooperation has become a central aspect of innovation management—alliances have evolved to be viewed as strategic necessities (Cassiman and Veugelers, 2006; Martínez-Noya and Narula, 2018). This is mainly caused by the fact that despite rising R&D expenses, drug development pipelines in the pharmaceutical industry have decreased in volume and continue to decline, which Hörner (2020) describes as a productivity paradox. Morgan Stanley (2010) have created a term for a business model with

[1] The definition industry practitioners have commonly used is that biotechnology firms develop and market biologic drugs and are founded after *Genentech* in 1976 (Nicholson et al., 2005), which were the first firm to produce biologic drugs. In practice, many biotechnology firms develop both biologic as well as chemical compounds (Nicholson et al., 2005). Almost half of the drugs on the licensing market during the study's time period were biologics. However, to increase readability, we refer to both as the pharmaceutical industry.

growing reliance on external R&D: *Search-and-Develop (S&D)*. There are firms in the pharmaceutical industry that, for example like *GlaxoSmithKline*, spend almost half of their R&D budget on external technologies (Palermo et al., 2019). Reepmeyer (2006) argues that increased reliance on external R&D comes with challenges. Balancing tasks that remain inside the organizational boundaries and tasks that are transferred to other parties has become one of the central issues in R&D and innovation management.

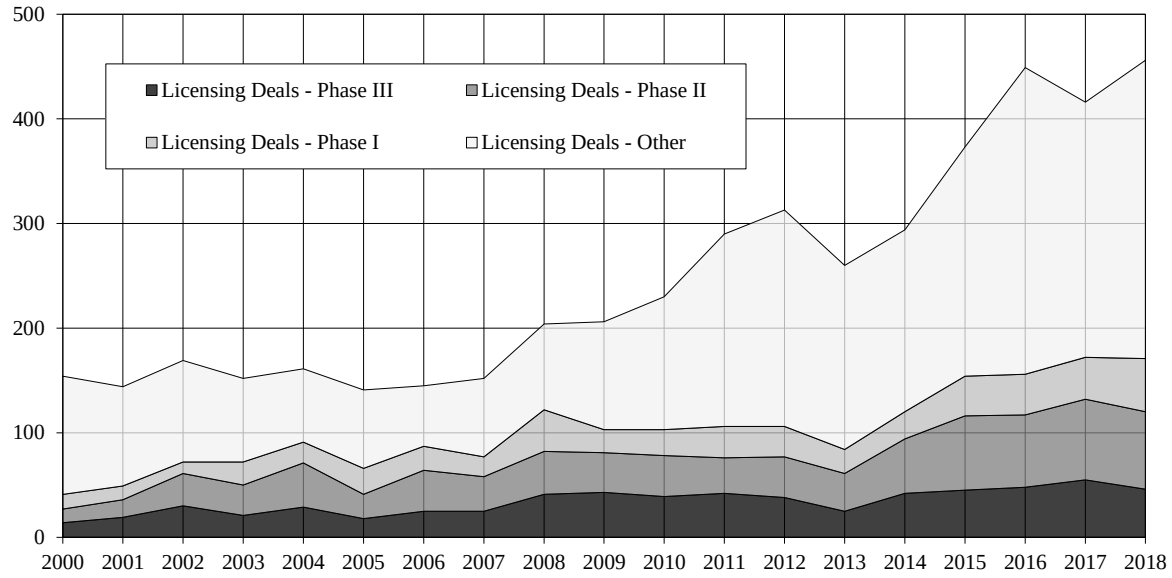
This narrative of such an innovation crisis, however, has been subject to criticism. Light and Lexchin (2012) argue that the true innovation crisis in the pharmaceutical industry is caused by the fact that firms focus on creating new variations of already existing drugs. In fact, by benchmarking against placebo, by circumventing hard clinical outcomes or by simply being inferior to competitor drugs, drugs that might be less effective or safe than existing treatments reach the market. They argue that estimates of average R&D costs are inflated and used to lobby for protection measures such as governmental subsidies. Light and Lexchin (2012) propose that the narrative of unsustainable R&D is a ploy given that revenues in the industry have increased more than average development costs have.

2.2 LICENSING IN THE PHARMACEUTICAL INDUSTRY

Licensing is the most common way to access innovation in the pharmaceutical industry besides in-house drug development (Gassmann et al., 2016). Licensing is a type of alliance between firms—most notably in technology-intensive sectors. Generally, the licensee gets permission to produce and commercialize one or several drugs through a licensing agreement with the licensor (Hagedoorn and Hesen, 2007). The form of these contracts tends to be very complex and often exceeds one hundred pages (Lerner et al., 2003). Kim and Vonortas (2006) find that the importance of licensing has increased due to intensified competition caused by globalization, increasing technological change and outsourcing. As shown in Figure 1, the number of licensing deals of drugs in all development phases has historically increased

worldwide. By investigating out-licensing (i.e. a licensor selling rights to a drug) and in-licensing (i.e. a licensee purchasing these rights) simultaneously, it is possible to present insights into their respective potential to create value (Walter, 2012). Additionally, since value creation is not independent of value appropriation, it is important to analyze interactions between determinants of value creation (Adegbesan and Higgins, 2010). Lavie (2007) provides a definition and distinction between value creation and value appropriation: "Value-creation mechanisms are collective processes that generate common benefits that are shared by all partners in an alliance, whereas value-appropriation mechanisms determine the distribution of these common benefits to individual partners as well as the capacity of partners to unilaterally extract private benefits that are unavailable to other partners" (p. 1191).

Figure 1: Historic Development of Licensing Deals per Development Phase



Source: Bloomberg Intelligence

2.2.1 OUT-LICENSING

According to Reepmeyer (2006), out-licensing allows a licensor to exploit R&D projects without having to bear some of the major risks associated with these projects. Thus, the licensor can extract value from internal research that would otherwise have been sunk. Lerner et al. (2003) note that small biotechnology firms tend to fund R&D through alliances when it is more

difficult to receive financing through public markets. Licensing agreements are commonly used to penetrate markets that the firm could not access on its own. Simonet (2002) proposes in a *Licensing Management Matrix* (as can be seen in Table 2) that the two determinants of out-licensing are: (1) resources of the licensor; and (2) the size of the target market. Essentially, if the licensor has a weak resource base, out-licensing is a recommended activity regardless of the size of the target market. Similarly, if the firm has a strong resource base, it should not out-license as it can market the drug on its own. However, if it possesses an average resource base, then it should only out-license if the target market is too big for the licensor to handle by itself.

Table 2: Licensing Management Matrix

	Small Market	**Average Market**	**Large Market**
Strong Resource Base	Internal Development	Internal Development	Internal Development
Average Resource Base	Internal Development	Internal Development Co-Development	Co-Development Co-Promotion Co-Marketing **Out-Licensing**
Weak Resource Base	Internal Development Co-Development Co-Promotion Co-Marketing **Out-Licensing**	Co-Development Co-Promotion Co-Marketing **Out-Licensing**	Co-Development Co-Promotion Co-Marketing **Out-Licensing**

Source: Simonet (2002)

In accordance with the *Licensing Management Matrix*, many pharmaceutical firms with large resource bases have long considered the value of out-licensing to be ambiguous, especially compared to research alliances, in-licensing and co-development (Gassmann et al., 2016). Windhover (2003) suggests that employees within large organizations are reluctant to commit to out-licensing as it is seen as less prestigious than in-licensing. However, Gassmann et al. (2016) deem that successful out-licensing programs can in fact provide benefits for large pharmaceutical firms in the form of additional revenue generation as well as an increase cost-effectiveness and further mitigation of R&D risks. Similarly, DiMasi et al. (2016) note the emergence of new alliances across all firm sizes. Albeit the rationale for out-licensing appearing to be clearly defined, Megantz (2002) argues that the decision for or against out-

licensing is not as obvious as it is often depicted as. For the development of a drug to be successful, a dedication of financial and personnel resources is required from the licensor.

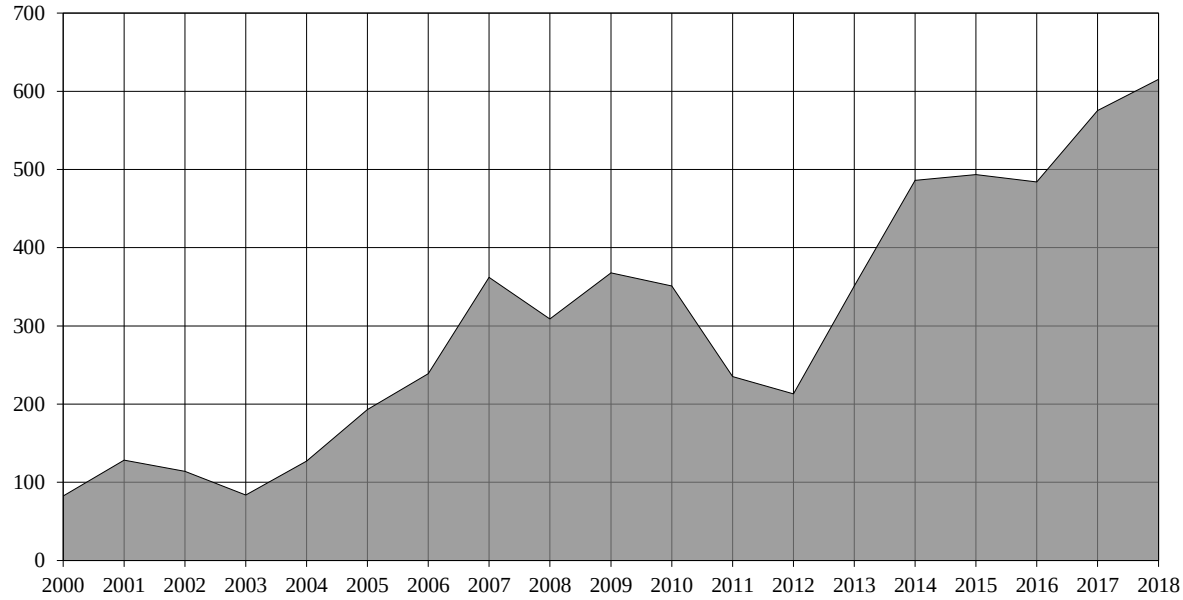
2.2.2 IN-LICENSING

Like out-licensing, in-licensing has emerged as a key value driver for many pharmaceutical firms. According to Reepmeyer (2006), it has mainly been recognized as a mechanism to reach corporate objectives. By in-licensing, the licensee can quickly expand their portfolio of potential drug candidates without inferring the risks and costs associated with an expansion of their R&D program. In-licensing can help firms keep up with technological advances and facilitate learning (Lowe and Taylor, 1998). Not only does in-licensing help the licensee reduce the risk of shortfalls in its own development pipeline, but also the risk of underinvestment in its own R&D infrastructure (Reepmeyer, 2006). This can be especially valuable when firms face future patent expirations (Grabowski and Kyle, 2012).

The importance of in-licensing has increased rapidly. Up to 80% of R&D pipelines of large pharmaceutical firms emanate from external sources, of which many are gained from licensing agreements (Gassmann et al., 2018). Between 2000 and 2018, the market for licensing has expanded significantly, as can be seen by observing average amounts pharmaceutical firms spend per in-licensing deal (see Figure 2). To be precise, the global, average value of a licensing deal has grown from USD 82.70 million in 2000 to over USD 600 million as of 2018. This corresponds to an annual compounded average growth rate of roughly 12%. This increase in value derives mainly from an increased bidding competition for promising drugs (Gassmann et al., 2018). Due to scarcity, companies have started to increasingly consider in-licensing of early-stage drug candidates, commercially comparably unattractive late-stage drugs, and niche products that generally include higher risk (Gassmann et al., 2018). It appears that the pharmaceutical market for technology transfer can be described as very healthy in the sense of

activity. An expansion of technology markets generally allows firms to boost their performances by combining different technological inputs (Palermo et al., 2019).

Figure 2: Historic Development of Licensing Deal Values



Source: Bloomberg Intelligence

2.2.3 LICENSING VALUATION

The earlier in the development process the licensing takes place, the more difficult it is to accurately compute future revenue streams (Paetz and Reepmeyer, 2003). In fact, Bogdan and Villiger (2010) deem valuating early-stage licensing contracts to be one of the most difficult tasks in financial life sciences. They state that the value of a deal splits itself into three distinct forms of payment from the licensee to the licensor: (1) an upfront payment; (2) milestone payments; and (3) a royalty agreement. The upfront payment is a lump sum payment, which is usually paid when the licensing agreement is signed. Milestone payments are contingent on reaching pre-defined goals in the development of the drug, while royalties are contingent on the potential revenues the drug generates. During licensing negotiations, two issues are central: (1) the fair value of the project; and (2) how this value should be distributed between the three aforementioned payment types (Crama et al., 2008).

It is often ambiguous how a contract should be structured so that it is considered a fair deal for both parties. The notion of a fair deal is tied to a value share principle in which the licensor gains and the licensee retains a certain percentage of the fair deal value (Bogdan and Villiger, 2010).[2] Bogdan and Villiger (2010) state as a rule of thumb that the licensee should get a smaller share of the deal value the closer the drug is to the market. On a more granular level in the licensing contract, it is effectively the loss or gain of control over the asset that determines the share of deal value. These *pie-splitting control rights* can be divided into four groups: (1) intellectual property rights; (2) rights regarding further licensing; (3) manufacturing rights; and (4) marketing rights (Adegbesan and Higgins, 2010).

2.2.4 EXAMPLE OF A LICENSING DEAL

In 2011, it was announced that the Swedish pharmaceutical firm *Camurus* struck an agreement regarding its drug delivery technology *CAM2029* with the Swiss pharmaceutical firm *Novartis*. In the agreement, *Novartis* secured the real option worth USD 10 million for its right to take on the responsibility for clinical development and global commercialization of *CAM2029*. *Camurus* would fund and retain control over the clinical development of the technology until the option would be exercised (Camurus, 2011).

In 2013, *Novartis* decided to exercise its option and enter a global licensing agreement regarding *CAM2029* for treatments of patients with specific types of cancers. *Camurus* viewed *Novartis* decision to acquire full commercialization rights as a key milestone in its firm history and as a validation of its technology and product development capabilities (Camurus, 2013). As Fredrik Joabsson explains: The deal had a relatively front-loaded payment structure, as the transaction value focused on the upfront and milestone payments rather than the royalty side. The total sum of potential milestone payments amounted to USD 700 million, while potential

[2] We thank Fredrik Joabsson of *Camurus* for highlighting this issue.

royalties were in the range of mid to high single-digits. As it was the first major licensing deal for *Camurus* it was an important validation of their technology, which could facilitate further licensing deals for products based on the same technology.

In 2018, *Camurus* regained development and commercialization rights for *CAM2029*. The decision by *Novartis* to return the rights is said to be based on commercial reprioritization of development programs rather than missing success of *CAM2029* (Camurus, 2018). The Swedish company however was happy to regain the rights to its delivery technology, as *Novartis* made significant investments bringing the product candidate to a *Phase III*-ready stage and decrease the overall development risk. As of today, *CAM2029* is being studied in *Phase III* with expected completion of this phase during 2021 (Camurus, 2019).

3. THEORETICAL FRAMEWORK

This chapter aims to illustrate the current research frontier regarding value creation and appropriation in pharmaceutical licensing deals. We begin by discussing value creation in alliance settings and how value is appropriated between the alliance partners—lastly framing it in bargaining perspectives. We continue our discussion of the contemporary research frontier by describing issues of information asymmetries in licensing. Contractual design is used to explain how adverse selection and moral hazard problems can be at least partially averted. We conclude by illustrating validation effects alliances have for firms without significant prior proof-of-concept based on signaling theory.

3.1 VALUE CREATION AND APPROPRIATION IN ALLIANCE SETTINGS

Do strategic alliances create value?[3] Previous research has used positive announcement returns as a proxy for future firm performance improvements—thus value creation (Anand and Khanna, 2000; Chan et. al, 1997; Das et al., 1998; Kale. et al., 2002; Koh and Venkatraman,

[3] We use a definition of Gulati (1998): "[An alliance is a] voluntary arrangement between firms involving [the] exchange, sharing, or co-development of products, technologies, or services" (p. 293).

1991; McConnell and Nantel, 1985). Despite the apparent popularity of strategic alliances amongst corporate CEOs (KPMG, 2019), there seem to be difficulties associated with actually creating value in alliances given the large number of firms that fail to create value from them (Anand and Khanna, 2000). Moreover, as many other activities besides alliances can have an influence on firm performance, it can be difficult to directly link alliances with value creation. Research related to the benefits of alliances shows mixed evidence (Gulati, 1998), thus alliances seem to be paradoxical. Although they appear necessary to secure competitive advantage and growth, they exhibit surprisingly low success rates (Kale and Singh, 2009). A large part of value creation in alliances is still unexplained, and there are still major opportunities for knowledge generation within this area (Bösecke, 2009).

3.1.1 DETERMINANTS OF VALUE CREATION

Several determinants of value creation, proxied as returns to alliance announcements, have been previously identified. These include firm size (Das et al., 1998; McConnell and Nantel, 1985), R&D intensity (Walter, 2012), business relatedness (Chan et al., 1997), the presence of pre-existing marketing and technological alliances (Koh and Venkatraman, 1991) and general alliance experience (Anand and Khanna, 2000; Chang and Huang, 2002).

Firm size and R&D intensity have been argued to be of competitive advantage in high-technology industries (Atuahene-Gima and Patterson, 1993; Fu and Perkins, 1995). Cohen and Levinthal (1989; 1990) suggest that large firms have several innovation advantages, such as economies of scale for R&D investments, learning advantages and complimentary assets that improve the exploitation of innovations gained through alliances. At the same time, these large firms suffer from being more rigid and bureaucratic, as well as having weaker managerial control. It has been discussed whether large firms or small firms are more effective innovators (Walter, 2012). Pisano (1997; 2006) has provided empirical evidence that questions the efficiency of the biotechnology industry, which has historically been dominated by smaller

firms. He found that there was no difference in the R&D productivity of small biotechnology and large pharmaceutical firms (Pisano, 2006). In fact, Arora et al. (2009) find that large pharmaceutical firms are even more innovative than recently founded biotechnology firms.

Compared to other industries, firms in pharmaceuticals and biotechnology incur the highest R&D expenses in absolute terms—boasting R&D intensity (European Commission, 2020). This high R&D intensity is a result of the complex process of drug development (Pfeiffer, 2000). Cohen and Levinthal (1990) contend that the firm's ability to absorb new technologies is largely a function of pre-existing related knowledge in that respective area. Investments in R&D thus not only generate new knowledge on their own, but also contribute to the firm's capacity to absorb technologies externally. As such, R&D intensity is argued to be positively correlated with the ability to in-license technologies. Additionally, Walter (2012) reasons that R&D intensity should be value creating for the licensor as well—companies that spend more on R&D should be capable in producing high-quality compounds that are in demand.

Koh and Venkatraman (1991) hypothesize that business relatedness influences value creation in alliance settings. They argue that alliances between firms from related industries will outperform those from unrelated ones, as former are able to exploit shared core competencies. This results in economies of scale and resource allocation efficiency. Additionally, Balakrishnan and Koza (1993) highlight that business relatedness reduces information asymmetries between partners as they then share common background knowledge. On the other hand, Lin et al. (2009) propose that business relatedness reduces the benefits that partners can derive from exploiting each other's expertise in complementary areas. Lerner et al. (2003) contend that latter is the reason why alliances between public firms with otherwise sufficient access to public equity markets are formed. Empirically, the evidence for value creation from business relatedness is mixed (Walter, 2012).

Kale et al. (2002) show that firms with licensing experience may establish a dedicated corporate function for licensing activities in order to obtain economies of scale. Firms entering an alliance generally benefit from their prior licensing experience as it leads to knowledge accumulation (Kale et al, 2002).[4] Besides from being able to create more value, firms with significant prior experience have been found to be perceived as more desirable as partners (Gulati, 1995).

Bösecke (2009) notices that although there has been prior research on the topic, determinants of value creation in strategic alliances have not been examined in a sufficient number of studies to be used in a meta-analysis, which generally requires at least three uses (Dalton et al., 2003). The research area has been described as fragmented (Wang and Rajagopalan, 2014). While many studies have investigated value creation in alliances, few have investigated the division of value between the partners (Adegbesan and Higgins, 2010). It is also important to acknowledge that stock returns proxy value creation and appropriation to shareholders. Thus, announcement returns reflect increased profit potential rather than increases in innovation, and therefore are insufficient for addressing the critique that most new pharmaceutical products provide few benefits for patients and therefore society (Light and Lexchin, 2012).

3.1.2 VALUE APPROPRIATION

Adegbesan and Higgins (2010) argue that determinants of value creation and value appropriation in alliances are not independent from each other. A resource-based view (see Table 3) has long been used to describe dependencies in inter-organizational relationships (Emerson, 1962; Benson et al., 1978). In this view, organizational survival depends on the ability to procure critical resources from the organization's environment. Uncertainty or constraints of critical resources create a dependence on resource providers (Emerson, 1962). Value appropriation is enabled by owning assets valued by others that are in limited supply

[4] We thank Martin Welschof of *BioInvent* for highlighting the importance of prior licensing experience.

(MacDonald and Ryall, 2004). Das et al. (1997) propose that there is usually an asymmetric dependence in technology exchanges. This is because larger firms usually seek out smaller, innovative firms, and not the other way around. This increases the relative bargaining position of the small partner. They find that announcement returns for alliances are negatively correlated with firm size, which supports their hypothesis that the smaller party appropriates superior value from an alliance.

Table 3: Views on Inter-Organizational Relationships

	Resource-Based View	**Relational View**
Unit of Analysis	Firm	Dyad or network of firms
Sources of Profit	Scarce physical resources Human resources Technological resources Financial resources Intangible resources	Relation-specific investments Knowledge-sharing routines Complementary resources Effective governance
Mechanisms that preserve Profit	Firm-level barriers to imitation, such as resource scarcity and property rights	Dyadic or network barriers to imitation, such as partner scarcity
Ownership of Rents	Individual firm	Collective

Source: Emerson (1962); Dyer and Singh (1998)

Dyer and Singh (1998) introduce a seminal concept of value creation with a relational view on alliances (see Table 3). Compared to the resource-based view, the unit of analysis is the alliance. They argue that alliances which share relation-specific assets, knowledge-sharing routines, complementary assets, and effective governance are a source for relational rents as well as competitive advantage.[5] This relational view implies a different strategy for profit maximization compared to a resource-based view. While the latter argues that an individual firm should protect valuable information to prevent information spillovers, a relational view suggests that sharing information with alliance partners may increase the overall competitive advantage of the alliance (Dyer and Singh, 1998).

[5] They adapt a definition for relational rents from Peteraf (1993): Returns that exceed a factor's short run opportunity cost; and are in excess over the returns to a factor in its next best use.

However, Adegbesan (2009) as well as Oxley and Silverman (2008) point out that it is unclear if, when and why alliance partners benefit from these shared relational rents. Moreover, whether relational rents are shared symmetrically between alliance partners, or whether one party benefits more than the other is unknown as well. Adegbesan and Higgins (2010) argue that while Dyer and Singh (1998) provide a theory of value creation in alliances, an explicit mechanism for the value distribution between the alliance partners is missing. The questions of who appropriates value, as well as when and why, are still a largely unresolved issue (Adegbesan, 2009; Lavie, 2007). Dyer and Singh (1998) acknowledge this issue themselves and see the distribution of relational rents in alliances as an avenue for further research.

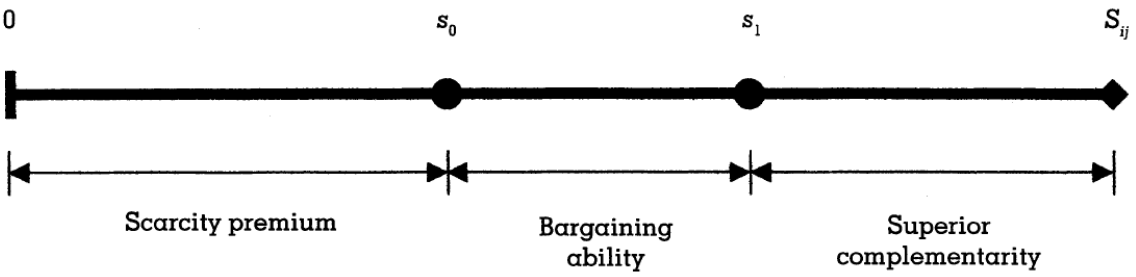
3.1.3 BARGAINING PERSPECTIVES

Lippman and Rumelt (2003) introduce a bargaining perspective on resources in interorganizational relationships. This perspective belongs to the resource-based view of the firm, which assumes that resources and capabilities are heterogeneous across firms (Peteraf, 1993). Their view on resources highlights that competitive advantage is obtained from possessing a resource that is viewed as either over-proportionally efficient or is valued in any other special way—creating scarcity. Moreover, the ability of the individual firm to create value from specific resources varies due the assumption that firms have heterogenous capabilities. Adegbesan (2009) builds upon the research of Dyer and Singh (1998) and Lippman and Rumelt (2003) by creating a model for bargaining power.

The bargaining perspective of Adegbesan (2009) suggests that the greater an agent's superior complementarity, relative scarcity or relative bargaining ability, the greater value it can appropriate from trading in strategic factor markets (see Figure 3). These are markets where firms buy and sell resources necessary to implement their strategies (Hirshleifer, 1980). Instead of focusing on the criticality of resources and organizational survival, the bargaining model deviates from a resource dependency theory by reflecting on matters such as innovation,

surpluses, and competitive advantages, rather than organizational survival and the criticality of resources and increases its appropriateness for related research (Adegbesan and Higgins, 2010).

Figure 3: Components of Surplus Split



Source: Adegbesan (2009)

In the model of Adegbesan (2009), matched firms are guaranteed a minimum level of value appropriation equivalent to their superior complementarity to a resource. Superior complimentary is defined as a combination of assets which results in a value surplus—it exceeds the value that could be generated by both parties independently. Due to superior complementarity, a firm will always capture at least some part of the surplus ($S_{ij} - S_1$). The second driver of value appropriation is relative scarcity. This refers to the relative supply and demand by seller and buyer groups. The firm that belongs to the group that is relatively scarcer will gain additional parts of the surplus (S_0). Lastly, a residual surplus ($S_1 - S_0$) is distributed according to the relative bargaining ability, which is defined as "all the means that agents might employ to cajole one another into parting with value" (MacDonald and Ryall, 2004).

3.2 INFORMATION ASYMMETRIES IN LICENSING AGREEMENTS

It is important to highlight the role of contractual design in licensing, given that this body of research is growing (Adegbesan and Higgins, 2010). Stiglitz (2000) highlights two types of information that are particularly characterized by asymmetric distribution: (1) information about quality; and (2) information about intent. In addition to information asymmetries between alliance partners, information asymmetries between the firms and their investors are also relevant, which are particularly pronounced for R&D-intensive firms (Aboody and Lev, 2000).

Information asymmetries are argued to be essential in order to explain abnormal returns in licensing (Nicholson et al, 2005). Bhattacharya and Ritter (1983) address the issue of how firms can signal the fair value of their growth opportunities. Contractual licensing design under asymmetric information is introduced in a model by Gallini and Wright (1990) including a clearly defined principal-agent problem: "The design of a licensing contract that maximizes profit, given the potential for opportunism by both parties in the contract" (p. 147). They argue that the transfer of innovations through licensing can be as complex as the invention itself.

3.2.1 ADVERSE SELECTION

The principle of adverse selection has been articulated by Akerlof (1970), who used the automobile market to illustrate this issue. Individuals who wish to buy a car are unaware whether the car is of good or bad quality (i.e. a *Lemon*). However, after owning a specific car for a certain length of time, the car owner (i.e. the seller) has a better understanding of the underlying quality of the car. This creates an information asymmetry between potential buyers and sellers. Buyers are not ready to pay full price for a car, as their unable to assess whether the car is of good quality. Thus, owners of good cars are unwilling to offer their cars for sale. All cars that are left for sale will be of bad quality (i.e. the *Lemon-Hypothesis*).

Pisano (1997) has tested the *Lemon-Hypothesis* in accordance with Gallini and Wright's (1990) principal-agent problem, where the licensor is an informed party with informational advantage. Like the example provided by Akerlof (1970), asymmetric information can drive out pharmaceutical projects with good prospects and leave only projects of bad quality available in the licensing market. In fact, Pisano (1997) argues that most drug development projects turn out to be *Lemons*, given that only a small fraction of drugs reach the market. Consistent with the *Lemon-Hypothesis*, Pisano (1997) finds that licensed development projects have higher failure rates than non-partnered projects. Similarly, Guedj (2005) observes that drugs developed by biotechnology firms but financed by large pharmaceutical firms are also more

likely to fail. On the other hand, Danzon et al. (2005) find that drugs are more likely to succeed in clinical trials when developed in alliances, while Arora et al. (2009) note that drugs licensed prior to clinical trials perform equally well as in-house R&D projects.

Another perhaps more complicated adverse selection issue has been described by Crama et al. (2008). They also consider the licensor to be the informed party with informational advantage. They argue that licensing in pharma is a seller's market, which means that the licensor has a superior bargaining position compared to the licensee. However, due to incomplete information, opportunistic licensees will understate their estimate of the value of a deal in order to obtain more favorable terms. In their model, the licensor is the principal, unaware of the agent's (i.e. licensee's) fair valuation of the project. Hence, the licensor is facing adverse selection despite being better informed on the true quality of the drug. They also argue that the issue of incomplete information in pharmaceuticals is harder to deal with compared to other settings, as pharmaceutical projects are generally more likely to fail than succeed.

3.2.2 MORAL HAZARD

Besides information about quality, the second type of information which is particularly affected by an asymmetric distribution is information about intent (Stiglitz, 2000). The issue of potential moral hazard in licensing emerges as the actual level of effort alliance partners exhibit cannot be included in the contract. It is generally believed that more efficient outcomes can be reached by cooperating. However, the most prevalent assumption in related literature is that agents behave in a non-cooperative way (Macho-Stadler and Pérez-Castrillo, 1991).

Like adverse selection, a moral hazard issue can be framed in different ways. Kitch (1977) noted that patents rarely disclose the real value of inventions. This is because any disclosure of the secret behind the invention would naturally reduce its value. The owner can disclose such information protected by the framework of patent rights, which is referred to as know-how or trade secret licensing. Macho-Stadler et al. (1996) found that most licensing agreements specify

such transferal of know-how, which is deemed a potential source of moral hazard. They argue that the moral hazard problem stems from both the non-verifiable nature of the transmitted asset as well as the licensor's low incentives to disclose know-how. Additionally, it is not easy for the licensee to monitor the licensor's behavior when it comes to transmitting know-how. This issue has also been phrased as inventor moral hazard: The fact that inventor cooperation is most important for the success of development projects (Jensen and Thursby, 2001).

Another moral hazard has been raised that affects the licensee (Higgins, 2007; Lerner and Merges, 1998). The licensee needs to ensure that funds they may provide to small biotechnology partners are not allocated to other research projects. The complexity and unpredictability of R&D makes it difficult to contractually specify the obligations of the licensor. It can be very difficult for the licensee to ensure that the licensor has not employed resources towards other research projects (Lerner and Merges, 1998).

For the licensor, Dechenaux et al. (2009) highlight the issue of licensee shelving, which is the reluctance to develop or commercialize the drug, despite having ownership. Shelving can be intentional as well as unintentional. Intentional shelving can be compared to a monopolist situation with sleeping patents (Gilbert and Newbery, 1982), in which inventions are (temporarily) not put to commercial use—for example due to strategic reasons, such as product cannibalism. The risk of shelving is particularly acute in deals with high royalties, which reduce the licensee's incentive to develop and commercialize the drug (Murphy et al., 2012).

3.2.3 CONTRACTUAL DESIGN

Contractual design can help mitigate issues of adverse selection and moral hazard in licensing (Crama et al., 2008). Much research has been done with a two-part tariff contract with a fixed component and a variable component (i.e. a royalty agreement) (Beggs, 1992; Gallini and Wright, 1990; Macho-Stadler and Pérez-Castrillo; 1991; Macho-Stadler et al., 1996). The presence of royalties is viewed as a mitigator of information asymmetries between the licensor

and licensee. The inclusion of royalties can be used to signal a good innovation, since agreeing to them demonstrates the licensor's confidence in the innovation. Royalties raise the licensor's incentive to transfer know-how to the licensee (Macho-Stadler et al., 1996) and show effort towards the development of the drug (Higgins, 2007).

The two-way tariff contract has been expanded upon by Crama et al. (2008) and Dechenaux et al. (2009). Both introduce a three-part tariff contract that includes an upfront payment, milestone payments as well as royalties. The inclusion of milestones is considered more consistent with actual business practice. Dechenaux et al. (2009) note that while theoretical literature on licensing is extensive, it is focused primarily on simple, two-part contracts involving a fixed payment and royalties. They show that these simpler contracts prove to be suboptimal in the presence of adverse selection and moral hazard issues. Milestones can be used to solve moral hazard problems on both sides. They can mitigate the risk of the licensor withholding valuable know-how as well as licensee shelving.

Crama et al. (2008) propose that the inclusion of a royalty agreement can be problematic for the licensor. This is a consequence of product sales and resulting royalty payments being conditional on the licensee's marketing efforts. Under moral hazard, the royalties will act like a tax on the licensee and reduce the incentive to invest as commercial upside is shared with the licensor. When moral hazard is likely, the licensor should substitute royalties for milestone payments. Therefore, milestones can act as a discriminating element that signals the licensor's confidence in the product without reducing the licensee's incentives to invest.

3.3 SIGNALING THEORY AND VALIDATION EFFECTS

The validation role of alliances has been highlighted as a solution to mitigate information asymmetries between firms and investors (Nicholson et al., 2005).[6] Perrow (1961) notes that organizations regularly claim to have high-quality products, but with "increasingly complex and specialized goods and services many potential consumers cannot adequately evaluate these claims" (p. 337). He argues that these quality claims can however be validated by a third person with appropriate experience and resources. Spence (1973) proposes that signals can be produced and used to reduce information asymmetries between firms and investors. Signals require a better-informed party to provide an indication of quality.

Signaling theory has been applied to a wide range of disciplines (Bird and Smith, 2005). Leland and Pyle (1997) introduce signaling intermediaries as a solution to information asymmetry problems. The signals these intermediaries produce can distinguish high-quality from low-quality firms. They argue that without such information transfer, markets perform poorly. Therefore, such information transfer must occur for projects of high quality to receive financing. This information transfer can be facilitated through a credible intermediary, which "buys and holds assets based on its specialized information" (p. 383).

Theory of intermediaries as signalers has evolved from being exclusive to financial market settings to other settings as well. Stuart et al. (1999) introduce a certification role of alliances. They show that the alliance partner plays an important role for biotechnology start-ups. By entering an agreement with a prominent alliance partner, the biotechnology firm sends a signal to outside investors that the start-up is of high quality. They argue that this certification role can be substantial given the high degree of uncertainty in biotechnology research.

[6] This section could have also been named *Certification* based on Stuart et al. (1999).

Like Stuart et al. (1999), Nicholson et al. (2005) propose that pharmaceutical firms can have a validating role in alliances with biotechnology firms. They suggest that the role of an intermediary with specialized information buying and holding assets matches pharmaceutical firms that search for drugs for in-licensing. If investors have less information regarding the success of the biotechnology firm's products than the pharmaceutical firm, then the biotechnology firm can signal its quality by entering a licensing agreement with the pharmaceutical firm. They find that private biotechnology firms signing their first alliance deal receive a 47%-discount in deal value compared to those that have signed at least two prior deals. This is consistent with their hypothesis that biotechnology firms that benefit most from validation will be willing to pay for it by accepting a discount in deal value. Moreover, as the biotechnology firm receives a discount, they are not in fact a *Lemon* that exploits an information advantage over the licensee about the quality of their drug candidate. This evidence challenges Pisano's (1997) hypothesis that out-licensed drugs are *Lemons*.

Palermo et al. (2019) study the licensing market for patents and suggest that the validation theory provided by Nicholson (2005) could serve as an alternative explanation for their results. They observe that high-quality technologies with superior patent reliability were acquired by licensees with above average resources and capabilities. As such, they hypothesize a pecking order in the licensing market, where licensors target firms of the highest perceived quality or reputation. Below-average licensees may then be selecting from left-overs in the market.

Dacin et al. (2007) argue that the legitimization function—defined as when an actor is validated or endorsed—has been largely overlooked as a specific benefit of alliances. In fact, it might have a profound impact on the economic and competitive success of both the firm and the alliance. They propose a theoretical framework of five different legitimacy needs in the form of market legitimacy (as a firm in a certain market), relational legitimacy (as a potential alliance partner), social legitimacy (in a social or institutional context), investment legitimacy (for

internal constituents and financial stakeholders) and alliance legitimacy (of the alliance as a business activity). Thus, Dacin et al. (2007) make an important contribution by addressing mechanisms of alliance legitimization as well as why it is important for firms. We acknowledge however that validation in the analysis of pharmaceutical compounds is defined as the proof of suitability for the intended purpose. This is an important part of the registration application for a new drug (Ermer, 2001). The concepts of pharmaceutical validation and the certification role of alliances are overlapping but do not necessarily refer to the same concept, even though the latter is also often called validation.

Lastly, it is crucial to mention that Wang and Rajagopalan (2014) point out a causality problem between value creation and value appropriation, namely that there has been no attempt to isolate the distinct mechanisms in a systematic way. Adegbesan and Higgins (2010) acknowledge this issue and consider it to be desirable to capture these dynamics more explicitly. For value creation, Wang and Rajagopalan (2014) argue that the two most important challenges are (1) the degree of complimentary resources and (2) the mitigation of information asymmetries. For value appropriation, the main challenges are (1) the allocation of control and (2) ex ante safeguards against moral hazards such as misappropriation and holdups in development. Nevertheless, the distinction between value creation and value appropriation is disputed. Whereas Wang and Rajagopalan (2014) consider asset complementarity to be value-creating, it is a determinant of bargaining power and value appropriation in the model of Adegbesan (2009). We address the issue of causality by regarding mechanisms that serve to reduce ex ante information asymmetries as value creation, while considerations related to bargaining perspectives and contractual design that mitigate the risk of ex post moral hazard are considered to be value appropriating.

4. HYPOTHESES DEVELOPMENT

This chapter illustrates the hypotheses our study is testing—including their derivation. We start by developing our base hypothesis that licensing in the pharmaceutical industry creates value and that this value is mostly appropriated by the licensor due to scarcity issues. Following this, we create further, more detailed hypotheses regarding (1) bargaining perspectives and validation effects, (2) contractual design, (3) further intricacies of contractual design, and (4) issues of information asymmetry-induced adverse selection.

4.1 VALUE APPROPRIATION AND SCARCITY

To our knowledge, two papers study announcement returns from licensing deals specifically: Anand and Khanna (2000) and Walter (2012). Higgins (2007) studies announcement returns from technology transfer agreements but with a primary focus on the transfer of control rights. The lack of empirical research on value creation from pharmaceutical licensing deals is acknowledged by Walter (2012). Inferior data availability could be an underlying issue. As of 2009, there only was a small number of alliance databases, with only two covering the pharmaceutical and biotechnology sectors: *RECAP* and *Bioscan* (Schilling, 2009). Aforementioned research as well as research on alliance announcements (Chan et. al, 1997; Das et al., 1998; Kale. et al, 2002; Koh and Venkatraman, 1991; McConnell and Nantell, 1985) suggests that positive announcement returns can be expected for both the licensor and licensee. Consistent with the notion that licensors benefit from their scarcity (Crama et al., 2008), we expect licensor returns to be on average higher than that of licensees—for all combinations of firm size. From a bargaining perspective, scarcity should notch value appropriation towards licensors. This scarcity is supported by an increase in average deal values and upfront payments since 2000. Moreover, as 2015 to 2019 have shown favorable access to funding through public equity markets, the choice to enter an alliance should have been less influenced by financial concerns. It is also important to acknowledge that our event study framework is only capable

of observing listed firms, which have already resolved initial proof-of-concept issues and thus have superior access to equity funding compared to private firms (Lerner et al., 2003).

Hypothesis 1a: *Licensing deals create value and licensors appropriate a preponderance.*

4.2 BARGAINING PERSPECTIVES AND VALIDATION EFFECTS

For the licensor, we argue that value appropriation should be negatively correlated with firm size due to an asymmetric dependency in licensing, where smaller innovators have a superior bargaining position over larger firms (Das et al., 1998). Small research-intensive firms may often boast innovation advantages which are coveted (Scherer, 1999). This hypothesis is consistent with results from O'Connell et al. (2014) that contradict the apparently wide-spread assumption that large pharmaceutical firms' prey on small companies in licensing deals. For the licensee however, returns should be positively correlated to its own firm size, as it suggests superior capabilities related to late-stage marketing and commercialization and thus superior asset complementarity (Reepmeyer, 2006; Walter, 2012). This is consistent with the notion of alliances being based on comparative advantages (Kyle and Grabowski, 2012).

Hypothesis 2a: *Firm size reduces licensor and increases licensee value appropriation.*

Firm size of the partner however serves as a proxy for the signal-strength of validation effects. O'Connell et al. (2014) argue that demand by large pharmaceutical firms inflates an asset's perceived market value. In unreported regressions, Higgins (2007) finds that announcement returns for small biotechnology firms entering technology exchange agreements with large pharmaceutical firms are 7.01% on average. Returns for the large pharmaceutical firms in these respective deals are 1.06% on average. These findings suggest a strong validation signal

whenever a small firm engages in licensing with a large firm. These signals are likely to be perceived to be credible, as alliance agreements are time-consuming and costly to negotiate and implement for both sides (Lerner et al., 2003). Large public firms have been found to have more R&D projects in their pipelines and thus more R&D expertise than non-public and small public firms (Rothaermel and Deeds, 2004), which is why an alliance affiliation with larger firms potentially creates a validation signal for other R&D projects in the pipeline of the small firm or the firm as a whole. We hypothesize that this validation effect is also present for small licensees entering a licensing agreement with large licensors. In the end of 2019, *BioInvent* entered an agreement with *Merck* in which former was the licensee. The collaboration was described to be "an excellent validation of [*BioInvent's*] work and scientific excellence" by their CEO (BioInvent, 2020). As the validation effect mostly serves to address information asymmetries between the firm and its investors, it is considered to be value creating and not value appropriating (Wang and Rajagopalan, 2014). It effectively causes a value increase that the licensor could not achieve on its own. Naturally, the validation can occur at the expense of less favourable deal terms (Nicholson et al., 2005).

Hypothesis 2b: *The size of the licensing partner positively correlates with value creation.*

R&D spending improves assimilation capabilities of external technologies (Cohen and Levinthal, 1990), while also increasing learning and innovation (Mowery et al., 1996). External R&D gained through alliances is complementary and not a substitute to in-house R&D—thus, increases overall innovation performance (Hagedoorn and Wang, 2012). As such, we hypothesize that an increase in licensee R&D spending increases their asset superiority and thus ability to appropriate value. For the licensor, it has been found that licensees generally value extensive R&D pre-experience (Hoang and Rothaermel, 2005). Adegbesan and Higgins

(2010) propose that R&D firms with validated technologies are more likely to discover new, promising drugs. Additionally, they argue with reference to Leland and Pyle (1977) that the existence of previous R&D projects shows that the firm has been able to raise funding for such projects in the past. Thus, R&D intensive licensors appear as more attractive to licensees. Walter (2012) also suggests that R&D intensive firms are more likely to possess drugs which are in demand. Therefore, R&D intensity of the licensor should increase its asset complimentary as well.

Hypothesis 2c: *An increase in R&D intensity increases respective value appropriation.*

Lerner et al. (2003), Higgins (2007) as well as Adegbesan and Higgins (2010) find that the financial strength of the licensor increases their bargaining ability in exchanges for technology control rights. In fact, they find that it is the single most important factor impacting the allocation of these rights. Thus, we predict that financial strength or rather available liquidity of the licensor will positively impact their returns, as it can be used to proxy for bargaining ability. Moreover, licensors with low financial strength could enter licensing deals due to liquidity concerns and therefore lose their scarcity premium. We argue that liquidity could be a relevant proxy for the bargaining ability of the licensee as well—especially as we not only observe large licensees. O'Connell et al. (2014) argue that small- and medium-sized licensees are typically financially constraint and end up with lower-quality assets as a result. They are also more willing to in-license high-risk drug candidates for their lower price tag. Therefore, we hypothesize that constraint licensees forego attractive assets on the licensing market due to their inability to offer attractive conditions and thus are less capable of appropriating value.

Hypothesis 2d: *An increase in financial flexibility improves respective value appropriation.*

4.3 CONTRACTUAL DESIGN

A minority of firms publicly disseminates information regarding the payment structure of licensing deals but based on empirical research (Higgins, 2007; Lerner et al., 2003; Nicholson et al., 2005) and theoretical research (Crama et al., 2008; Dechenaux et al., 2009), we argue that contractual design can be a major determinant of value creation and appropriation. As pointed out by O'Connell et al. (2014), understanding the buying behavior of corporations is crucial to comprehend the dynamics of the licensing market for drugs. Higgins (2007) finds that the announcement of milestone payments positively impacts returns of the licensee on a 10%-significance level. He argues that milestone payments condition payments of the licensee to the licensor on achieving pre-defined steps in the development of the drug, which is viewed favorably by investors. In unreported regressions, he on the other hand finds that the presence of an upfront payment positively impacts licensor returns as well. O'Connell et al. (2014) suggest that the relative size of the upfront payment is correlated with the quality of the drug. When the upfront payment is high, the interpretation could be that the licensee has acquired a valuable drug. However, milestone payments reduce moral hazard issues on both sides (Dechenaux et al., 2009), and the upfront payment can have a negative impact on the deal value (Crama et al., 2008). We propose that the ratio of the upfront to milestone payments should positively correlate with licensor returns, while negatively correlating with licensee returns.

Hypothesis 3a: *An increase in the ratio of the upfront payment to milestones impacts licensor value appropriation positively, while negatively impacting that of the licensee.*

We hypothesize that the total size of the deal value should create a validation effect based on expected commercial potential. Based on the theory of specialized intermediaries (Beggs, 1992; Leland and Pyle, 1997), the deal value should send a positive signal about the quality of

the development project and the licensor's capabilities because the licensee possesses expert knowledge and provides the market with credible signals, when it is willing to pay the licensor a large deal value. A large deal value could suggest a lower product risk as well as a large target market (O'Connell et al., 2014). Thus, large deals should create value in themselves, whereas the ratio between upfront and milestone payments increases or decreases value appropriation. It is important to consider that neither royalty rates are included in the deal value, nor that this deal value is risk-adjusted.

For the licensee, it is important to take the *blockbuster imperative* into consideration. Large pharmaceutical firms have traditionally focused their marketing and sales efforts on few, high volume so-called *blockbuster drugs* with at least one billion dollars in annual sales (Reepmeyer, 2006). *Blockbuster drugs* are a central growth driver for most leading pharmaceutical companies (Gassmann et al., 2018) in the context that few drugs generate revenues that exceed their development costs, while 20% of the products account for 70% of revenues (Reepmeyer, 2006). Only few firms globally appear to possess the large-scale marketing and sales capabilities required to commercialize *blockbuster drugs* (Hannigan et al., 2013). This suggests that these licensees hold superior complementarity towards assets that have very large potential target markets, and therefore create superior value for the alliance. As such, we hypothesize that the licensee generally benefits from entering more valuable licensing agreements as they thereby secure access to innovations that could potentially cover their development costs. Nonetheless, the *blockbuster imperative* does not guarantee that the drug is of high quality but just that it is perceived to be of high value by the licensee.

Hypothesis 3b: *The size of the deal value positively impacts value creation for both parties.*

4.4 INTRICACIES IN CONTRACTUAL DESIGN

Through an option agreement, the licensor has the right to regain rights to the product from the licensee (Bogdan and Villiger, 2010).[7] These agreements have become increasingly popular in recent years (Papp and Walton, 2010). When a project does not fit into the licensor's product development pipeline, it may be licensed out. However, with a *call-back option*, the licensor can regain control over the drug upon exercise. *Novartis*, for example, typically includes these *call-back options* in all its out-licensing contracts in order to mitigate the risk of underestimating a drug's potential (Gassmann et al., 2016). The large, multinational pharmaceutical firm *Roche* typically includes a *call-back option* when licensing out to smaller partners. A possible reason for the existence of *call-back options* between large pharmaceutical firms and small licensors could be a differential in bargaining power, favorizing the former (Reepmeyer, 2006). Exercising these real options comes at a cost, and most in fact expire (Papp and Walton, 2010). As these options are said to mitigate issues of moral hazard by the licensee and reflect licensor bargaining power, we hypothesize that *call-back options* could positively influence value appropriation by the licensor. However, although they mitigate information asymmetries of intent of the licensee, we argue they also weaken the power of validation signals as option agreements postpone partnering decisions (Papp and Walton, 2010). This signal of insecurity could potentially offset benefits from reduced information asymmetries. As we expect the lost validation effect to be more severe than the gain in value appropriation, option agreements should be viewed less favorably than similar licensing deals.

Many licensing agreements relate to a specific geographic region, such as Europe, North America, Asia-Pacific or a combination of markets. A licensor may assess a licensee to have sufficient capabilities in one geographical region but insufficient ones in others (Mendes,

[7] We thank Fredrik Joabsson of *Camurus* for highlighting this issue and the use of *call-back options* as a potentially valuable risk management tool for an alliance manager.

2000). Generally, the larger the market for a good, the higher value of the innovation (Aghion and Tirole, 1994). There are however other considerations. Global agreements are often formed because it is more lucrative for the licensee to fund the development of the asset when they can gain geographically unconstrained rights. The licensee is then able to fully leverage economies of scale in marketing and commercialization (Reepmeyer, 2006), which could indicate superior asset complementarity. For the licensor, we suspect that the risk of licensee shelving is reduced when latter obtains global rights and that it sends a validation signal. Additionally, a transfer of global commercialization rights effectively eliminates searching costs in other markets. However, the licensee might pay for markets it is unlikely to exploit (Mendes, 2000).

Hypothesis 4a: *Option agreements reduce licensor value creation, while global agreements increase it. Latter also positively influences licensee value creation.*

Licensing agreements often include a so-called R&D pledge, in which the licensee pledges to take over parts of or all the licensor's development costs (Bogdan and Villiger, 2010). For the licensor, this means that they can advance the drug usually much faster and without funding issues. For the licensee, it means that they gain more control over the drug as they can now assure that the development of the project proceeds in accordance with expectations. Such co-development agreements are meant to share development risks and costs between the parties (Gassmann et al., 2018). However, R&D pledges can simultaneously increase issues of moral hazard by the licensor for the licensee (Higgins, 2007). As larger public firms on average have more R&D projects (Rothaermel and Deeds, 2004), we hypothesize that the larger the partner firm, the less value will be created for the licensee from pledging R&D investments due to aforementioned moral hazard issue. On the other hand, we also expect R&D pledges to send a

positive validation signal for the licensor as the pledge shows confidence of the licensee in the capabilities of the licensor and the drug itself.

Hypothesis 4b: *R&D pledges increase licensor value creation. The size of the licensor in R&D pledges correlates negatively with licensee value creation.*

The licensor may often be better suited to innovate, while the licensee's resource base allows them to commercialize said innovation (Reepmeyer, 2006). Thus, licensing agreements usually include the explicit transfer of commercialization rights, which could create a positive validation signal regarding the development capabilities of the licensor and the quality of the underlying compound. This confidence of the licensee should positively impact announcement returns of both the licensee and licensor. Higgins (2007), however, argues that the market seems to reward the party that retains control over its drug. Although a transfer of commercialization rights makes sense given the notion of comparative advantages (Kyle and Grabowski, 2012), it is not obvious how the market will react when licensors forfeit control.

Hypothesis 4c: *The larger the licensee, the larger the licensor value creation from transferring commercialization rights. However, value is also created for the licensee.*

4.5 INFORMATION ASYMMETRIES

In early-stage licensing deals, information asymmetries are amplified considering that uncertainty of development success is the major contributor to these asymmetries (Aboody and Lev, 2000) and failure is concentrated to early-stage development efforts (Banerjee and Siebert, 2017). Licensees generally possess inferior information on the quality of the development project compared to licensors. This is particularly pronounced for drugs in the *Preclinical*

Phase (Nicholson et al., 2005) as it is difficult to value pharmaceutical compounds without clinical proof-of-concept (Bogdan and Villiger, 2010). Furthermore, there is also Pisano's (1997) *Lemon-Hypothesis* to take into consideration, which could bear relevance given the contemporary increase in attrition rates (DiMasi et al., 2016). In accordance with it, one could suspect that drugs offered for early-stage licensing mostly consist of *Lemons* that are opportunistically licensed out due to particularly severe information asymmetries. However, given descriptions of rigorous due diligence in licensing deals (Lerner and Merges, 1998; Reepmeyer, 2006; Rhodes et al., 2003), this seems somewhat implausible. Arora and Gambardella (2010) suggest that the *Lemon-Hypothesis* in the market for drug licensing has been overemphasized. As such, we alternatively hypothesize that out-licensing in an early stage will generate a strong validation signal, as the licensee signals confidence in the quality of the drug and thus reduces information asymmetries between the licensors and their investors. Several studies suggest that information asymmetry is negatively related to firm value (Anderson et al., 2009; Barth et al., 2013; Fu et al., 2012). Thus, we assume that the market discounts early-stage drug candidates to a larger extent than late-stage drug candidates, resulting in validation signals from licensing to be more significant for former.

The licensee can be expected to overcome information asymmetries with rigorous due diligence, which has shown to be the case for acquisitions in the pharmaceutical industry (Higgins and Rodriguez, 2006). The licensing due diligence process can usually last up to several months after an optimal partner has been identified (Reepmeyer, 2006). This supports the view that licensees are generally well informed (Beggs, 1992) as well as the idea of specialized intermediaries (Leland and Pyle, 1997). The licensee is incentivized to conduct due diligence as it helps uncover significant problems and generally increases value created from the agreement (Rhodes et al., 2003). This hypothesis is not entirely uncontroversial, however. Higgins (2007) argues that licensors hold bargaining power over licensees for late-stage drug

candidates as these are scarcer. Kalamas and Pinkus (2003) suggest that there is a price tag premium involved for late-stage drug candidates and argue that licensing in early stages could be value creating for licensees.

Nevertheless, we reason that licensing in early stages is less likely to exhibit positive NPV for licensees compared to later stages as comparative advantages—late-stage development, marketing, and commercialization—are less relevant (Grabowski and Kyle, 2012). Furthermore, licensees must commit significantly more financial resources to develop and commercialize a compound in early stages compared to later stages (DiMasi et al., 2016). Vice versa, late-stage licensing should exhibit a reversed relationship, creating more value on average for licensees than for licensors. Late-stage licensing will be beneficial for large licensees, as they possess superior asset complimentary towards late-stage development and commercialization (Reepmeyer, 2006). When it comes to the licensor, it is not entirely clear whether out-licensing in a late stage is beneficial or not. The rationale for late-stage licensing has been argued to be dependent on the resource base of the licensor (see *Licensing Management Matrix*). Therefore, late-stage licensing should be less beneficial for licensors that have large asset bases. This suggests that their opportunity cost is larger compared to small and medium-sized firms, considering they have the improved capabilities to take the drug to the market by themselves.

Hypothesis 5a: *Early-stage deals positively correlate with licensor value creation, while late-stage deals are value-destroying. This relationship is reversed for licensees.*

Lastly, Higgins and Adegbesan (2010) argue that it is important to consider the technical risk of a drug when investigating value appropriation. As attrition rates are highly sensitive to the therapeutic area of the drug (Hay et. al., 2014; Thomas et. al., 2016; Wong et al., 2018), it is of

interest to explore how these potential differences in information asymmetry influence value creation and appropriation. Given that the high attrition rate in oncology is well researched, we argue that support for Pisano's (1997) *Lemon-Hypothesis* could be found in this therapy area as it is the one in which drugs are expected to fail most often.

Considering that validation signals are especially beneficial when information on quality cannot be easily verified (Kotha et al., 2018), the strength of validation signals is assumed to be positively correlated with the degree of information asymmetry between the licensor and their investors. A strong validation signal should be present for oncology drugs, as it has the highest attrition rate of all therapeutic areas. The large market for cancer treatments (EvaluatePharma, 2019) in combination with low success rates could suggest a high sensitivity of the licensor's market value to changes in the market's perception of their drug. Thus, we hypothesize that oncology deals will positively influence licensor returns due to relatively stronger validation signals.

Additionally, we argue that areas of special interest in the drug market may provide benefits of scarcity to the licensor—in addition to stronger validation signals. Many *blockbuster deals* between 2015 and 2020 involved drugs in immuno-oncology.[8] It has quickly become the fastest growing specialty therapeutic area in the pharmaceutical industry (Hoos, 2016). In 2019, immuno-oncology displayed the highest number of R&D projects under development of all specialty therapeutic areas (Pharmaproject, 2019). Immuno-oncology drugs could therefore reflect situations in which the licensor is able to create as well as appropriate value from the licensee due to scarcity, considering that more and more pharmaceutical firms want to position themselves within this field (Pharmaproject, 2019). In accordance with aforementioned

[8] The concept of using the immune system against cancers dates back to at least the mid-nineteenth century. Immuno-oncology encompasses a broad range of drug types, such as antibodies, peptides, proteins, and small molecules. Since the regulatory approval of *ipilimumab* (*Bristol-Myers Squibb*) in 2011, the field of cancer immunotherapy has experienced a renaissance (Hoos, 2016).

bargaining perspectives, the licensor should be able to capture a scarcity premium on top of asymmetrically generated value from validation. This study's therapeutic focus on oncology treatments echoes their dominance between 2015 and early-2020 (Pharmaproject, 2019). The high prevalence of immuno-oncology, however, could indicate that it is in fact not scarce enough to demonstrate any value appropriation.

Hypothesis 5b: *Oncology and immuno-oncology deals depict licensor value creation and value appropriation, respectively.*

Table 4: Overview of Hypotheses

Value Appropriation and Scarcity	**Hypothesis 1a**: *Licensing deals create value and licensors appropriate a preponderance.*
Bargaining Perspectives and Validation Effects	**Hypothesis 2a:** *Firm size reduces licensor and increases licensee value appropriation.* **Hypothesis 2b:** *The size of the licensing partner positively correlates with value creation.* **Hypothesis 2c:** *An increase in R&D intensity increases respective value appropriation.* **Hypothesis 2d:** *An increase in financial flexibility improves respective value appropriation.*
Contractual Design	**Hypothesis 3a**: *An increase in the ratio of the upfront payment to milestones impacts licensor value appropriation positively, while negatively impacting that of the licensee.* **Hypothesis 3b**: *The size of the deal value positively impacts value creation for both parties.*
Intricacies of Contractual Design	**Hypothesis 4a**: *Option agreements reduce licensor value creation, while global agreements increase it. Latter also positively influences licensee value creation.* **Hypothesis 4b**: *R&D pledges increase licensor value creation. The size of the licensor in R&D pledges correlates negatively with licensee value creation.* **Hypothesis 4c**: *The larger the licensee, the larger the licensor value creation from transferring commercialization rights. However, value is also created for the licensee.*
Information Asymmetries	**Hypothesis 5a**: *Early-stage deals positively correlate with licensor value creation, while late-stage deals are value-destroying. This relationship is reversed for licensees.* **Hypothesis 5b**: *Oncology and immuno-oncology deals depict licensor value creation and value appropriation, respectively.*

5. DATA AND DESCRIPTIVE STATISTICS

This chapter describes the origin of the data set we are using, its structure, and the quality of its entries. We show in which ways we manipulate the given data set in order to create variables, which are useful for statistical analysis. Further, including appended firm-specific variables, this chapter evaluates the representativeness of our sample for the global population of licensing deals in the pharmaceutical sector, identifies potential bias and, based on this, draws conclusions for our empirical methodology and the validity of our results. For this, we create summary statistics and compare them against an external source.

5.1 SAMPLE CREATION

We use the *Bloomberg Intelligence Global Pharma* function to obtain a data set of licensing deals recorded between 01-Jan-2015 and 19-Mar-2020. To the best of our knowledge, this data set represents the most expansive and detailed contemporary source on global licensing activity in the pharmaceutical industry available to us. The data set is a proprietary creation of *Bloomberg L.P.* and its research arm *Bloomberg Intelligence* and is based on information from official company press releases and regulatory agencies. It is crucial to mention that licensing databases are generally a valuable and reliable tool only when sample limitations are acknowledged. Related research should be designed in a manner that makes best use of a database's strength, while highlighting potential weaknesses (Schilling, 2009).

5.1.1 DATA STRUCTURE

The data set we obtain consists of 4,335 licensing deals and primarily contains their announcement dates as well as the names and stock tickers of the licensor and licensee. In addition, it also lists a plethora of variables related to different aspects of the licensing deal, such as its payment structure and the underlying pharmaceutical compound. Variables that describe the payment structure for example include the size of the upfront payment, the total deal value and information on the royalty agreement. Variables that describe the underlying drug for example include its broad therapy area, its indication (i.e. disease it is supposed to treat) and its development phase. A complete overview and explanation of all variables present in the source data set can be taken from Table 5.

Table 5: Source Data Variables

	Variable	Description
	Announcement Date	Announcement date of the licensing deal
Firm Identifiers	Licensor Name	Legal name of the licensor
	Licensee Name	Legal name of the licensee
	Licensor Ticker	Stock ticker of the licensor
	Licensee Ticker	Stock ticker of the licensee
Information on the Drug	Broad Therapy Area	Broad definition of the targeted disease
	Indication	Narrow definition of the targeted disease
	Product	Name of the drug / technology
	Special Interest	Areas of research which are especially sought after
	Development Phase	Current development phase of the drug
Contractual Design	Upfront Payment	Value of the upfront payment
	Total Deal Value	Sum of the upfront payment and all potential milestones
	Royalty	Description of the royalty agreement
	Option Agreement	Presence of a *call-back option*
	R&D Pledge	Pledge by the licensee to provide R&D funding
	Commercialization Rights	Geographic region of commercialization rights

5.1.2 DATA QUALITY

We must place good faith in *Bloomberg Intelligence* to gather and enter information available to them to the best of their knowledge and capability.

Primarily, it is apparent that not all observations contain values for each variable. This does not surprise us, as parties of a licensing deal are not obliged to disseminate information regarding all variables. Nonetheless, the omission of variables raises the question whether these omissions have an underlying pattern, which inherently biases the sample. The parties of the licensing deal could be inclined to disseminate favorable information deliberately and voluntarily, whereas keeping unfavorable information private. This would bias inferences made on the data set, as the sample over-represents favorable information.

In general, the range of many discrete variables seems to be arbitrary. It is unclear why *Bloomberg Intelligence* choose to define exactly 14 broad therapy areas or why they choose to define exactly six areas of special interest. However, we suspect that this reflects conventions in the industry. Variables that contain information on the drug are generally consistent to those included in studies on attrition rates (Hay et al., 2014, Thomas et al., 2016; Wong et al., 2018). Furthermore, it is unclear why the data set includes exactly the variables it includes. Again, we argue that this can be based on the availability of data from press releases, which follow

industry conventions and thus include information that is generally perceived to be useful from an industry and general stakeholder perspective. Naturally, a lot of focus has been directed towards identifying parts of the dataset that may be suitable for this study.

Lastly, and possibly most implicit for the results of our study, we note, as data entries are made manually, that the overall quality of entries is imperfect. Although we are able to manually correct typographical errors and other minor mistakes for many variables, including, for example, licensor and licensee stock tickers, which sometimes belonged to subsidiaries or already-acquired firms instead of the actual economic beneficiary, we must acknowledge that information on the royalty agreement is entered in an inconsistent and granular way, which prohibits detailed use in statistical analysis. As the variable takes on 474 unique values, we argue that a manual conversion, for example, into binary variables that describe different aspects of the royalty agreement, is hardly possible. Thus, further use of information on royalty agreements inherent in the licensing deals in our study is not possible. We acknowledge that this has implications on contractual design hypotheses as an expansion beyond upfront and milestone payments would have likely added empirical value.

5.1.3 REPRESENTATIVENESS

Although we base our sample on the most expansive and detailed contemporary source on global licensing activity in the pharmaceutical industry available to us, we must discuss its ability to represent the global population of licensing deals fairly. Gelman and Hill (2006) argue that the most important regression assumption is that the sample data accurately reflects the phenomenon of interest. They consider this to be an often-overlooked matter in research.

Because we use an event study framework based on cumulative abnormal returns, our sample is reduced to firms listed on stock exchanges at the time of the announcement. Private firms however represent a significant part of the global population. As thereby all our sample firms

are expected to have better-than-average access to public equity funding compared against the population average, this introduces a significant bias to our sample.

We furthermore count 496 licensing deals in which the licensor or licensee is a non-commercial entity—university or charity. Although these deals are unambiguously part of the global population, it is ambiguous whether determinants of value creation and appropriation from these deals are comparable to those between two commercial entities. Because our hypotheses development implicitly assumes a value-maximization framework for both alliance partners, we exclude these observations from our sample as they could induce heterogeneity.

Additionally, we notice that 369 licensing deals include multiple licensors or licensees. Because our event study framework cannot properly consider licensing deals with multiple parties on either side of the agreement, we exclude these observations.

Moreover, a major drawback of our sample is its temporal limitation, as it does not include any information on licensing activity before 01-Jan-2015. Even under the assumption that our sample includes the total global population of licensing deals since then, this creates a temporal sampling bias. Our sample is for example unable to factor in changes in idiosyncratic contracting behavior and industry conventions.

Another drawback is that the data might incorporate further limitations based on its availability and the sample thus might misrepresent licensing deals made in certain jurisdictions. As publicly disseminated information acts as the basis for the information in the sample, we suspect that the sample over-represents licensing deals made in jurisdictions with stricter informational disclosure requirements (either due to more rigorous regulatory agencies or more demanding stakeholders) against deals made in jurisdictions with more relaxed requirements. Parties in relaxed jurisdictions might furthermore selectively choose to disseminate favorable information voluntarily, which exacerbates aforementioned issues of over-representation of favorable against unfavorable information.

5.2 DESCRIPTIVE STATISTICS

It becomes evident that not all variables from the source data set can be immediately used in statistical analysis. We aim to convert as many of the affected variables into a usable format without changing their inherent informational content. Not all variables created during this chapter are meant to be used in our study but rather to discuss whether there is any bias inherent in the data set. For example: A possible over-representation of licensing deals made in recent years, as data collection efforts by *Bloomberg Intelligence* might not have been consistent. We use the announcement date to create binary variables of calendar years, consequently, look at their summary statistics, and compare them against an external source.

We convert broad therapy areas into 14 unique binary variables. We assign these variables only if the broad therapy area is given and unambiguous. We use a similar approach for development phases and research areas of special interest. Latter are furthermore grouped into immuno-oncology, gene therapy and other special interests as only the first two show more than 20 observations. We convert option agreements, R&D pledges, and general transferal of commercialization rights into binary variables.

We further create the ratio of the upfront payment to the sum of milestone payments implied by the total deal value. However, we notice that the respective values are only given for a sub-sample of 720 observations. We acknowledge that the availability of these values might be directly influenced by the size of both the upfront payment and the total deal value. Larger values might be published more readily than smaller ones, as they ceteris paribus convey favorable information for at least one of the parties.

Regarding the geographic region of commercialization rights transferred, we create binary variables. We create variables for observations in which they are given explicitly and exclusively for the following regions: (1) Global, (2) Europe, (3) Asia-Pacific, and (4) North

America. We find that agreements generally have either global coverage or for one of the aforementioned regions exclusively.

Lastly, we append firm-specific variables by using the *Bloomberg Applications Interface* to obtain said variables in *Microsoft Excel* in order to identify potential size or industry bias. We use both the number of employees and sales as a proxy for firm size. For the number of employees, we use values reported in the last available quarter prior to the announcement of the licensing deal. For sales, we use values in USD million from the last available year. We obtain the sub-industry of both parties given by the *Global Industry Classification Standards* (*GICS*). A list of all variables can be taken from Table 6.

Table 6: Sample Variables

	Variable	Description
	Y_*	Calendar year variables
Broad Therapy Areas	AAI	Allergy, autoimmune and inflammatory
	Cancer	Cancer
	CM	Cardiovascular-metabolic
	CNS	Central nervous system
	Dermatology	Dermatology
	Drug Delivery	Drug delivery
	Gastrointestinal	Gastrointestinal
	Genitourinary	Genitourinary
	Haematology	Haematology
	Infectious	Infectious
	Musculoskeletal	Musculoskeletal
	Ophthalmic	Ophthalmic
	Respiratory	Respiratory
	Women's Health	Women's health
Areas of Special Interest	Immuno-Oncology	Immuno-oncology
	Gene Therapy	Gene therapy
	Other Special Interest	Other special interests
Development Phases	Preclinical	*Discovery* and *Preclinical Phase*
	Phase I	*Phase I*
	Phase II	*Phase II*
	Phase III	*Phase III*
	Fully Developed	Fully developed drug
Payment Structure	Upfront Payment	Value of the upfront payment
	Milestone Payments	Value of all potential milestone payments
	Total Deal Value	Sum of the upfront payment and all potential milestones
	Upfront to Milestones	Ratio of the upfront to milestone payments
Further Contractual Design	Option Agreement	Presence of a *call-back option*
	R&D Pledge	Pledge by the licensee to provide R&D funding
	Commercialization Rights	Transfer of commercialization rights
	Global	Global commercialization rights
	North America	North America-exclusive commercialization rights
	Asia-Pacific	Asia-Pacific-exclusive commercialization rights
	Europe	Europe-exclusive commercialization rights
Firm Size Proxies	Sales Licensor	Last available sales figures for the licensor
	Sales Licensee	Last available sales figures for the licensee
	Employees Licensor	Last available employee numbers for the licensor
	Employees Licensee	Last available employee numbers for the licensee
Sub-Industries	GICS Pharma Licensor	GICS sub-sector pharmaceuticals for the licensor
	GICS Pharma Licensee	GICS sub-sector pharmaceuticals for the licensee
	GICS Biotech Licensor	GICS sub-sector biotechnology for the licensor
	GICS Biotech Licensee	GICS sub-sector biotechnology for the licensee

Table 7 shows summary statistics. We compare them to BIO (2019, p. 28-30), which gives insights on worldwide drug licensing activity for 2009 to 2018. The *Biotechnology Innovation Organization* (BIO) publishes a yearly report on investment and deal trends in biotechnology since 2015, which includes information on licensing, venture capital, IPOs, and M&A. These reports show statistics for licensing deals with values greater than USD 10 million only.

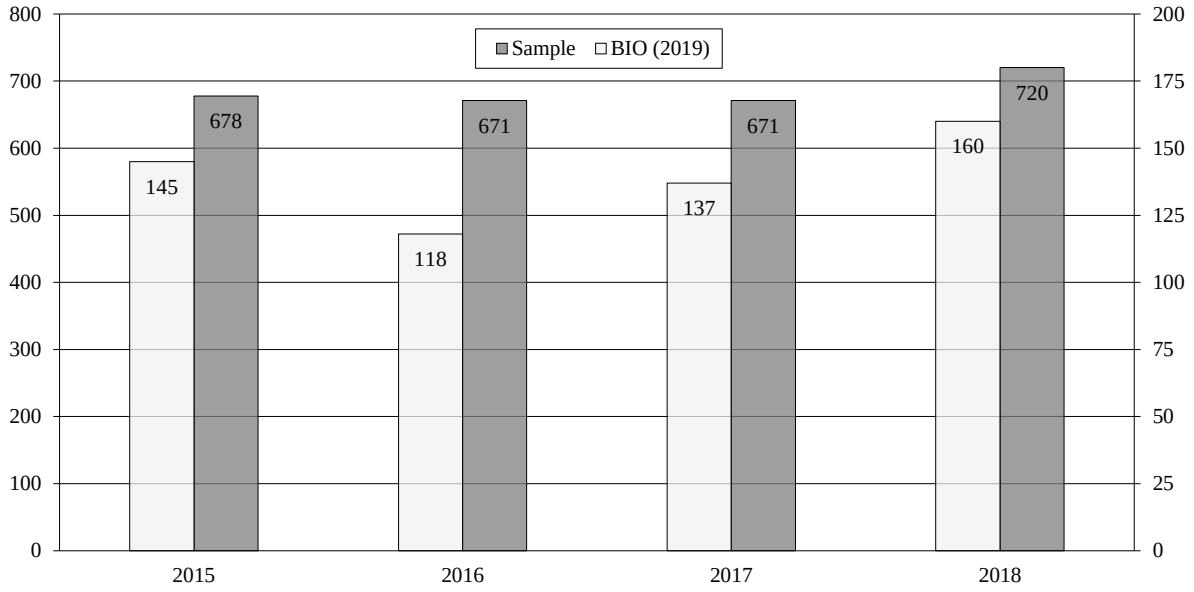
Table 7: Summary Statistics

	Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Years	Y_20	3451	.04	.197	0	1
	Y_19	3451	.166	.372	0	1
	Y_18	3451	.209	.406	0	1
	Y_17	3451	.194	.396	0	1
	Y_16	3451	.194	.396	0	1
	Y_15	3451	.196	.397	0	1
Broad Therapy Areas	AAI	2614	.077	.266	0	1
	Cancer	2614	.395	.489	0	1
	CM	2614	.126	.332	0	1
	CNS	2614	.13	.336	0	1
	Dermatology	2614	.017	.129	0	1
	Drug Delivery	2614	.026	.158	0	1
	Gastrointestinal	2614	.017	.129	0	1
	Genitourinary	2614	.016	.126	0	1
	Hematology	2614	.017	.129	0	1
	Infectious	2614	.079	.269	0	1
	Musculoskeletal	2614	.016	.126	0	1
	Ophthalmic	2614	.039	.195	0	1
	Respiratory	2614	.024	.153	0	1
	Women's Health	2614	.022	.146	0	1
Areas of Special Interest	Immuno-Oncology	3451	.101	.302	0	1
	Gene Therapy	3451	.032	.176	0	1
	Other Special Interest	3451	.046	.209	0	1
Development Phases	Preclinical	2848	.445	.497	0	1
	Phase I	2848	.091	.287	0	1
	Phase II	2848	.145	.352	0	1
	Phase III	2848	.118	.322	0	1
	Fully Developed	2848	.202	.401	0	1
Payment Structure	Upfront Payment	961	76.207	237.8	.04	3950
	Milestones	725	460.367	739.248	0	6900
	Total Deal Value	725	541.01	862.729	.95	8500
	Upfront to Milestones	720	.673	4.431	.001	109.375
Further Contractual Design	Option Agreement	3451	.051	.22	0	1
	R&D Pledge	3451	.782	.413	0	1
	Commercialization Rights	3451	.74	.438	0	1
	Global	1603	.422	.494	0	1
	North America	1603	.132	.339	0	1
	Asia-Pacific	1603	.245	.43	0	1
	Europe	1603	.056	.229	0	1
Firm Size Proxies	Sales Licensor	2401	5999.832	14794.5	0	233000
	Sales Licensee	2797	12342.13	19246.77	0	153000
	Employees Licensor	1866	15545	34961.94	1	750000
	Employees Licensee	2268	27119.52	39082.87	1	335000
Sub-Industries	GICS Pharma Licensor	2335	.362	.481	0	1
	GICS Pharma Licensee	2733	.537	.499	0	1
	GICS Biotech Licensor	2335	.544	.498	0	1
	GICS Biotech Licensee	2733	.431	.495	0	1

The sample divides roughly equally between calendar years (see Figure 4). Observation counts for 2015, 2016 and 2017 distribute themselves close to 670, while the observation count for 2018 is higher at 720 observations. For the years up to and including 2018, BIO (2019, p. 28) however shows a different distribution of licensing activity. Under the assumption that the

external source mirrors the true distribution of licensing deals, our sample over-represents observations from 2016, while under-representing observations from 2015 and 2018. However, our sample can in fact be expected to deviate from statistics shown in BIO (2019, p. 28), as it also includes licensing deals with deal values below USD 10 million.

Figure 4: Observations by Calendar Year

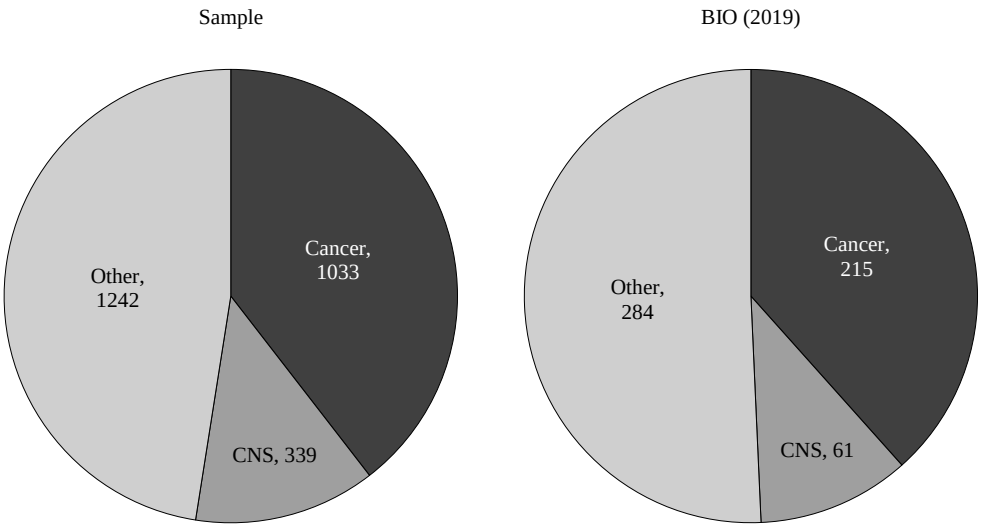


Source: BIO (2019, p. 28)

We notice that the deal count for 2019 deviates from prior years with only 572 observations. However, we argue that the observation counts in our sample approximately correspond to the general state of equity markets globally. Lerner et al. (2003) argue that small firms are more likely to enter alliances and licensing agreements when the availability of public equity financing is diminishing. This could also explain the high observation count for 2018.

When observing the distribution of observations between broad therapy areas (see Figure 5), it is evident that the sample is skewed towards oncology drugs. However, this is not surprising per se. BIO (2019, p. 30) shows that oncology, compared to other therapeutic areas, represented a relative majority of licensing deals made between 2015 and 2018 worldwide.

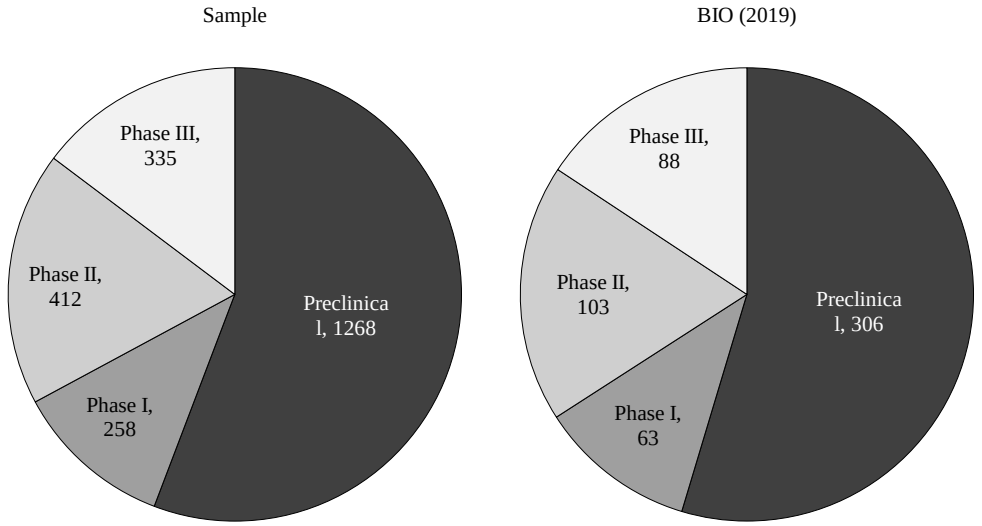
Figure 5: Observations by Broad Therapy Area



Source: BIO (2019, p. 30)

Furthermore, regarding development phases, we find that compounds in the *Discovery* and *Preclinical Phases* make up an absolute majority of the sample (see Figure 6), which is again supported by data we find in BIO (2019, p. 29).

Figure 6: Observations by Development Phase



Source: BIO (2019, p. 29)

We observe 764 values for total deal value (21.01% of the sample). We observe a minimum of USD 0.95 million and a maximum of USD 8,500 million with the latter relating to a strategic oncology collaboration between *AstraZeneca* (licensor) and *Merck* (licensee) announced in

2017 (AstraZeneca, 2017). Mean and median lie at USD 541.01 million and USD 245.00 million, respectively. BIO (2019, p. 29) shows a mean at USD 462.50 million. We attribute the fact that our mean is larger to an average total deal value of USD 637.01 million in 2019 and attribute the fact that our median is smaller to the fact that BIO (2019, p. 29) only includes licensing deals with a total deal value of more than USD 10 million in their statistics.

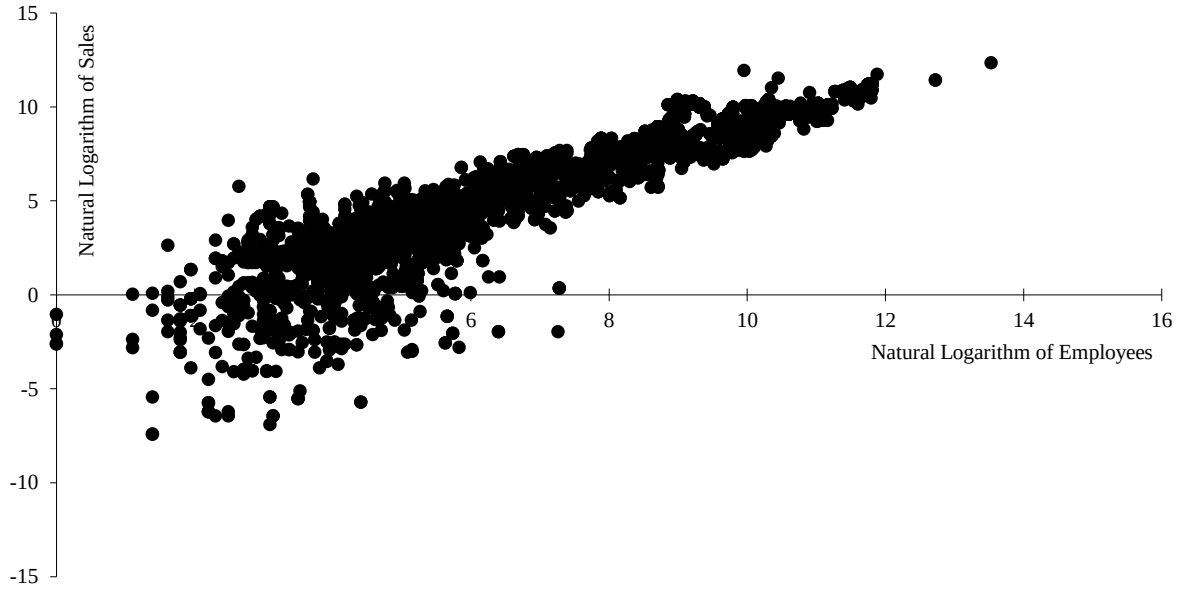
We count 961 observations for the upfront payment (27.85% of the sample). We observe a minimum of USD 0.04 and a maximum of USD 3,950 million with former relating to a research and development collaboration between *Galapagos* (licensor) and *Gilead Sciences* (licensee) announced in 2019 (Gilead Sciences, 2019). Mean and median lie at USD 76.21 million and USD 18.49 million, respectively. BIO (2019, p. 29) indicates a mean of USD 43.21 million but again we observe an average upfront payment in 2019 significantly above the sample mean.

For the ratio of the upfront payment to milestone payments, we count 720 observations (20.86% of the sample). We observe a mean of 0.67 (approximately a 2:3 ratio) and a median of 0.10 (approximately a 1:10 ratio). BIO (2019, p. 29) indicates an average ratio of 0.10, which confines to our sample median. We contribute this to the fact that our sample includes deals with a total deal value of less than USD 10 million, which show a ratio of 0.90 on average.

Furthermore, from 1,603 unambiguous values for the region of control rights transferred (46.45% of the sample), we create the four aforementioned variables. 42.23% of these observations are for global agreements, while 24.52% of the agreements are exclusively for Asia-Pacific, 13.23% for North America and 5.56% for Europe. In total, we find, that commercialization rights were transferred in 2,555 observations. The difference in the number of observations can be explained by the fact that some observations do not disclose the geographical region for which the rights are transferred.

In order to describe the size distribution of our sample companies, we look at sales and the number of employees. We find that sales range from zero to USD 232.89 billion with mean and median at USD 9.41 billion and USD 181.31 million, respectively. For employees, values range from one to 750,000. Mean and median lie at 21,895 and 1,302. Based on both, we notice that our sample includes firms of heterogenic sizes (see Figure 7), which implies that it covers a wide range of firm sizes found in the pharmaceutical industry, but acknowledge that this circumstance has to be considered appropriately in our empirical methodology, as determinants of value creation and appropriation might deviate between these categories of firm sizes.

Figure 7: Observations by Firm Size



We observe the sub-industry for 2,355 licensors and for 2,733 licensees, which corresponds to 67.66% and 79.19% of our sample. The split between biotechnology, pharmaceuticals and other industries is 54:36:9 for licensors and 43:54:3 for licensees (see Figure 8).

Figure 8: Observations by Sub-Industry

Thus, we can conclude that the source data set which we base our sample on is does in fact depict a mostly fair image of the global licensing market in the pharmaceutical industry for the time period covered. Relevant bias has been mentioned and has to be taken into consideration, nonetheless. Given our method, a limitation to listed firms cannot be averted. Overall, the descriptive statistics are encouraging given that alternative databases used in previous research have been criticized for representing skewed samples of the total population (Schilling, 2009).

6. EMPIRICAL FRAMEWORK AND METHODOLOGY

This chapter illustrates our event study methodology and our approach to testing aforementioned hypotheses. We describe the event by which we define value creation and show measures we take to increase the robustness of our results. We specify our regression models in detail; explain how we derive proxies and how we decide on control variables. Lastly, we list steps we take in order to increase the empirical validity of our results.

6.1 EVENT STUDY FRAMEWORK

According to MacKinlay (1997) event studies in economics and finance aim to measure the impact of specific events on the value of a firm. Under the assumption of an efficient marketplace, the effect of these events—the information on the value of the firm they convey

to market participants—should be reflected in the stock price of the firm in a timely manner. This implies that the impact of licensing deals on the value of firms can be measured by observing stock price effects in a narrow period around the announcement of said deals.

6.1.1 EVENT DEFINITION

Our event study observes the impact of the announcement of licensing deals in the pharmaceutical industry on the stock prices of the parties involved. Our selection criteria for including an announcement in our research approach are limited by the availability of data regarding these events. Our sample includes 3,451 observations. For 2,098 of these, we can observe stock prices for the licensor. Similarly, we are able to observe stock prices for the licensee in 2,508 observations.

6.1.2 ABNORMAL RETURNS

In accordance with MacKinlay (1997) and prior empirical research in the field (Anand and Khanna, 2000; Higgins, 2007; Walter, 2012), we wish to keep our standard event window as narrow as possible and thus define it as [± 1]. Expanding the event window beyond the announcement date is necessary in order to capture stock return effects occurring after the market closes on the announcement date (MacKinlay, 1997). An observation of the stock price prior to the announcement date furthermore allows us to consider the possibility of market participants acquiring and trading on information shortly before.

In order to quantify value creation caused by the underlying events studied, we require a measure of abnormal returns, which MacKinlay (1997) describes as observed stock returns less normal returns during the event window. Normal returns are defined as expected returns for the observed firm under assumption that the event had not occurred.

We utilize a market model to estimate normal returns during the event window. A market model relates the expected return of a stock to the return of a given market portfolio (MacKinlay, 1997). The return of a stock on a certain day is given as:

$$R_{x,t} = \alpha_x + \beta_x \times R_{m,t} + \varepsilon_{x,t}$$

, where the right-hand term is an OLS regression of daily stock returns on market returns during an estimation window prior to the announcement date. Thus, abnormal returns of a stock on a certain day during the event window are given as:

$$AR_{x,t} = R_{x,t} - \hat{\alpha}_x - \hat{\beta}_x \times R_{m,t}$$

In accordance with MacKinlay (1997) and aforementioned prior research, we utilize an estimation window with a length of 120 days with an additional 30-day buffer period between the end of the estimation window and the start of the event window. We argue that shorter estimation windows might be polluted by single, idiosyncratic movements of a given firm's stock. Longer event windows, however, are not suitable for two reasons. First, some observations do not have a trading history of significantly more than 150 days, and we wish not to include short-term IPO return effects in the estimation window. Second, longer event windows might not be appropriate to reflect the changing nature of small and fast-growing firms in our sample adequately, especially in biotechnology. We use a buffer period to account for information leakages in order not to pollute estimations of normal returns.

MacKinlay (1997) argues that an inclusion of post-event data in the estimation window can sometimes increase the robustness of normal returns estimations. However, we refrain from doing so because licensing might fundamentally change the business prospects of the involved firms and thus estimations of normal returns.

As for the choice of market portfolio, we argue that a suitable portfolio should appropriately mirror events, which are idiosyncratic to the pharmaceutical industry, and should also adequately reflect the fact that our sample includes firms of heterogenic sizes.

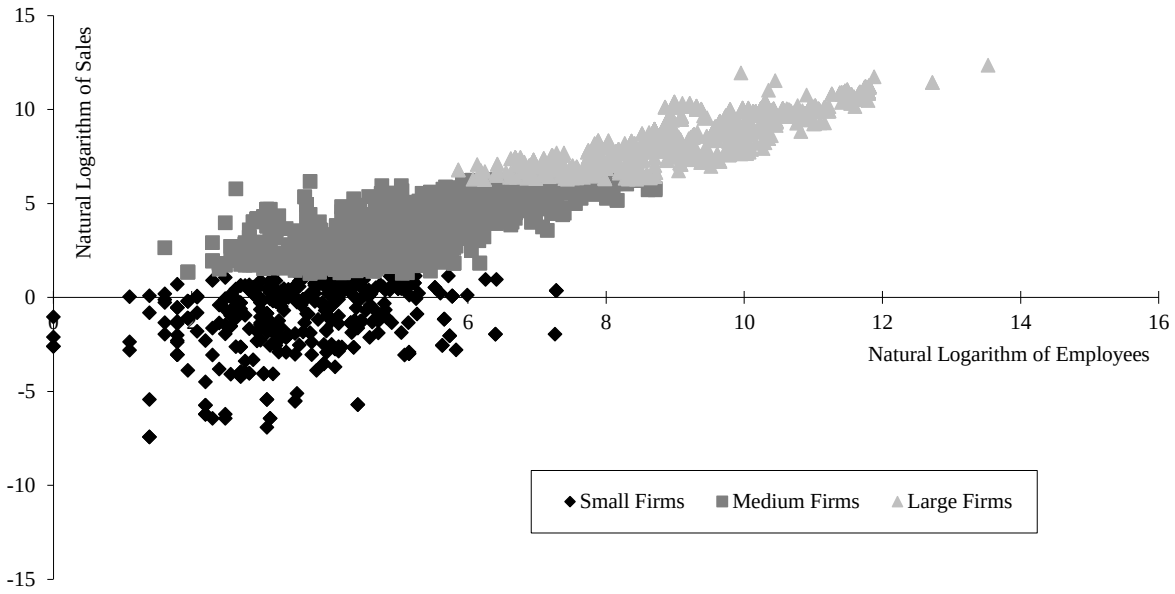
The former issue commands that we refrain from using broad-market indices, such as the *MSCI World Index*, as events idiosyncratic to the pharmaceutical industry would likely be specified as abnormal returns, at least partially, if they occur within the event window. This is the case because these idiosyncratic events would only partially affect returns of a broad-market index compared to fully affecting returns of an industry-specific index.

The latter issue commands that we cannot use established industry-specific indices, such as the *MSCI World Pharmaceuticals, Biotechnology and Life Sciences Index*. As our sample includes a wide range of firms found in the pharmaceutical industry, it includes firms of heterogenic firm sizes. The *MSCI World Pharmaceuticals, Biotechnology and Life Sciences Index* as well as other established industry-specific indices contain inherent bias towards larger firms. Aforementioned index for example consists of 77 firms with an average market capitalization of USD 47.09 billion—the minimum being USD 800.01 million (MSCI, 2020). The average market capitalization of our sample firms however lies at USD 41.04 million prior to the announcement. Thus, established industry-specific indices are not representative of our sample. Furthermore, as the index is weighted by float-adjusted market capitalization (MSCI, 2020), its returns are biased even further towards larger companies. Aside from being misrepresentative of our sample, weighting by market capitalization would create a reverse causality between abnormal returns and market capitalization.

To address previously described issues, we create equally weighted indices from our sample firms, which are rebalanced daily. In order to accommodate for size differences between our sample firms and thus often fundamental differences in their business models, we group all sample firms into three clusters based on firm size. We use the firm's sales figures as our main proxy for firm size. We do not use the aforementioned number of employees because we observe values for fewer firms than we observe sales for. We refrain from using value-based size proxies, such as market capitalization or enterprise value, to avert reverse causality

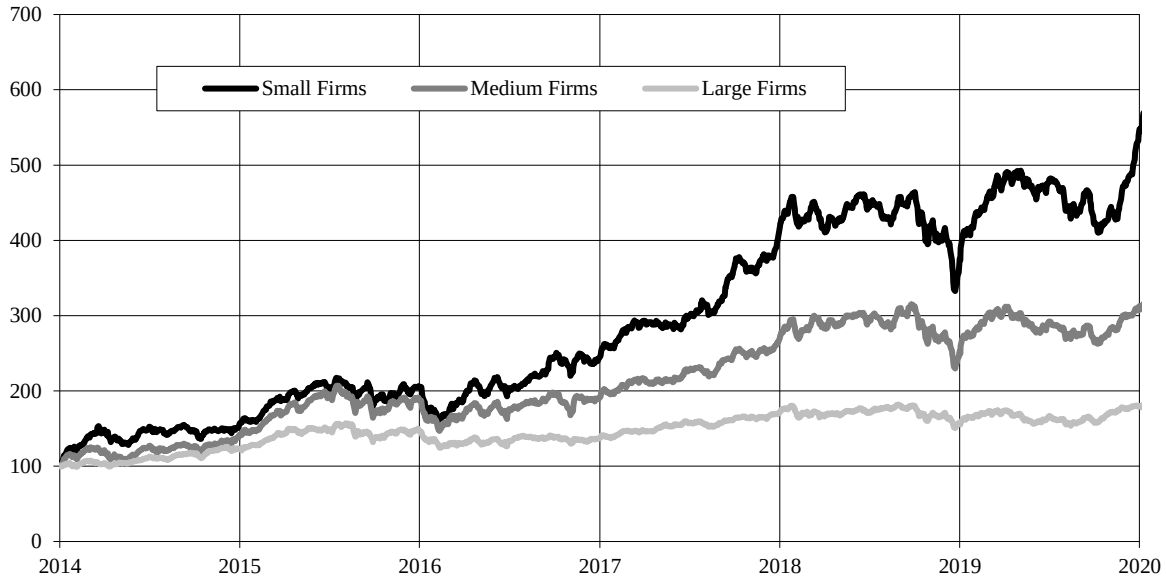
between firm size and abnormal returns. Using agglomerative hierarchical clustering, we group firms into clusters illustrated in Figure 9. We calculate dissimilarities on the Euclidian distance between them and agglomerate using Ward's method. The figure shows observations, for which we observe the number of employees as well as sales, in order to better illustrate clusters.

Figure 9: Firm Size Clusters



This leads us to have three equally weighted market indices, which act as market portfolios when computing abnormal returns for their respective member firms. The implied trading history of these indices between 01-Jan-2014 and 19-Mar-2020 can be taken from Figure 10.

Figure 10: Price Development of Market Portfolios



Based on the returns of these market portfolios, we can calculate abnormal returns of a firm on a certain day of the event window using aforementioned methods. Cumulative abnormal returns for company during the duration an event window are given as:

$$CAR_x(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{x,t}$$

Average cumulative abnormal returns for an arbitrary sub-sample are then given as:

$$\overline{CAR}(t_1, t_2) = \frac{1}{n}\sum_{x=1}^{n} CAR_x(t_1, t_2)$$

We compute average cumulative abnormal returns for licensor and licensees separately. Although in- and out-licensing represent two sides of the same contract, implications on the business prospects of the involved parties are fundamentally different. We furthermore compute average cumulative abnormal returns for size-based sub-samples as well—again for both sides separately. Lastly, we compute abnormal returns for further divided sub-samples, which take both the size of the licensor and the size of the licensee into consideration.

In order to test the statistical significance of results created, we conduct a t-test, which checks whether cumulative abnormal returns are different to zero. The t-test statistic is given as the ratio of average cumulative abnormal returns and their standard error.

6.1.3 ROBUSTNESS

We replicate aforementioned procedures, while changing certain aspects in our research design in order to increase the robustness of our results. First, we observe how abnormal returns behave using event windows of [± 2] and [± 3]. Second, we compute alternative abnormal returns using the following market portfolios: (1) three market portfolios based on firm size clustered by the number of employees; (2) a single market portfolio consisting of all sample firms; and (3) the *MSCI World Pharmaceuticals, Biotechnology and Life Sciences Index*. We note that results for the first alternative might deviate because we observe the number of employees less often than we do sales figures.

6.2 HYPOTHESIS TESTING

We analyze abnormal returns and their variation between observations—thus value creation and appropriation—by conducting ordinary least squares (OLS) regressions of explanatory and control variables against our measures of abnormal returns. This is consistent with previous research (Anand and Khanna, 2000; Higgins, 2007; Walter, 2012). We split the returns at their medians and conduct binary regressions as a robustness measure and find that OLS regressions appear to provide superior results. Nevertheless, there could be unobserved heterogeneity related to the process prior to when the deal is announced, such as competition, which the data set nor OLS can control for.[9]

[9] In a seminal paper, Boone and Mulherin (2008) show with the help of two-stage regressions that cross-sectional variation in the level of competition prior to the announcement has an impact on acquirer returns in M&A. In consistency with the notion of scarcity, it would be interesting to control for potential competition amongst licensees. This warrants the use of two-stage models, however adequate data is unavailable.

For hypotheses mentioned in Chapters 4.2 to 4.5, we create individual regression models. For **Hypothesis 1a**, we do not create a model as we test it by conducting t-tests. All models are specified using chapter-exclusive explanatory variables and a shared set of control variables.

Our models for hypotheses of *Bargaining Perspectives and Validation Effects* are specified as:

$$\overline{CAR}(t_1, t_2) = \alpha + \beta_1 \times \text{Firm Size} + \beta_2 \times \text{Partner Firm Size}$$

$$+ \beta_3 \times \text{R\&D Intensity} + \beta_4 \times \text{Liquidity} + \sum_{j=1}^{k} (\gamma_i \times \text{Control}_i)$$

When testing hypotheses of *Contractual Design*, we remain agnostic regarding the total deal value proxy. For each model specification, we test from the following three proxies which is the most meaningful: (1) the total deal value in USD million, (2) the total deal value in USD million squared; and (3) the natural logarithm of the total deal value in USD million. Models to test the hypotheses are specified as:

$$\overline{CAR}(t_1, t_2) = \alpha + \beta_1 \times \text{Upfront to Milestones}$$

$$+ \beta_2 \times \text{Total Deal Value} + \sum_{j=1}^{k} (\gamma_i \times \text{Control}_i)$$

When testing hypotheses of *Intricacies of Contractual Design*, we create two model specifications (i.e. four in total) because we observe the geographic region for which commercialization rights are issued for a sub-sample roughly half the size of the total sample:

$$\overline{CAR}(t_1, t_2) = \alpha + \beta_1 \times \text{Option Agreement} + \beta_2 \times \text{Global} + \sum_{j=1}^{k} (\gamma_i \times \text{Control}_i)$$

In the other specification, we include binary variables, for example for the presence of a R&D pledge, and interaction terms with the other party's firm size, to distinguish between a potentially linear effect of R&D pledges and validation effects based on the size of the licensing partner. Model are specified as:

$$\overline{CAR}(t_1, t_2) = \alpha + \beta_1 \times \text{R\&D Pledge}$$

$$+ \beta_2 \times (\text{R\&D Pledge} \times \text{Partner Firm Size}) + \beta_3 \times \text{Commercialization Rights}$$

$$+ \beta_4 \times (\text{Commercialization Rights} \times \text{Partner Firm Size}) + \sum_{j=1}^{k} (\gamma_i \times \text{Control}_i)$$

Our models to test hypotheses of *Information Asymmetries* are specified as:

$$\overline{CAR}(t_1, t_2) = \alpha + \beta_1 \times \text{Preclinical} + \beta_2 \times \text{Phase III} + \beta_3 \times \text{Cancer}$$

$$+ \beta_4 \times \text{Immuno-Oncology} + \sum_{j=1}^{k} (\gamma_i \times \text{Control}_i)$$

6.2.1 PROXY VARIABLES

We derive proxy variables based on firm-specific data we append using the *Bloomberg Applications Interface* in *Microsoft Excel*. Table 8 shows an overview of proxy variables.

Table 8: Proxy Variables

Variable	Proxy
Firm Size	Natural logarithm of sales
R&D Intensity	R&D divided by operating expenses
Liquidity	Cash divided by total assets

We use sales in USD 10,000 reported in the last available year prior to the announcement date as a proxy for firm size. As previously explained, we do not use the number of employees as we do not observe it as often as we do sales figures. We take the natural logarithm of the obtained values because we argue that an increase in sales by a fixed dollar amount does not have the same implications for firms with zero sales as it does for established firms with sizeable sales figures of for example more than one billion dollars annually. We do not use sales in USD millions as to avoid negative values for our firm size proxy. We furthermore add

a commemorative amount of USD 10,000 to all observations of sales in order to avoid issues with taking the natural logarithm for firms with zero sales. We also calculate the square of these values for potential use as a control variable.

In order to calculate R&D intensity, we obtain operating expenses and R&D expenses in a similar manner to sales. We divide latter by former and do not further modify the obtained ratio as it a distributed between zero and one by design. Both variables are significantly negatively correlated with sales, nonetheless, dividing by operating expenses is our preferred option as it keeps collinearity issues minimal, as opposed to dividing by sales for example.

Lastly, we obtain total assets and cash for the quarter prior to the announcement date. We divide latter by former in order to create a proxy for liquidity. As is the case with our R&D intensity proxy, we do not modify it any further.

6.2.2 CONTROL VARIABLES

We use a modelling technique called *general-to-specific modelling* (*GETS*) to derive skeleton models of control variables that possess necessary properties for correct inferences (Campos et al., 2005). Considering the lack of preceding empirical evidence regarding robust determinants of value creation and appropriation (Walter, 2012), the technique's agnostic properties have been considered valuable. *GETS*-modelling builds up on the notion that over-specification of models is more advantageous for the validity of results than underfitting (Baum, 2012). Generally, the idea is that a reversed modelling strategy starting with simple specifications and seeking to refine by adding variables is inherently flawed (*specific-to-general*) (Baum, 2012). The *GETS*-approach starts instead with a so-called *general unrestricted model* (*GUM*), which contains all possibly relevant variables and then continues by conducting a series of tests (Hoover and Perez, 2004). We use the *Stata command genspec*, created by Clarke (2014), to apply the *GETS*-approach to our data. It conducts five tests: (1) a *Doornik-Hansen Normality Test*; (2) a *Breusch-Pagan Test* for homoscedasticity; (3) a *Ramsey Regression Specification*

Error Test (*RESET*) for linearity of coefficients; and (4) an in-sample and out-sample stability test. If the *GUM* passes the tests, then an OLS regression is conducted, with a stepwise removal of the variable with the lowest t-test statistic (Clarke, 2014).

As the *GETS*-approach is a data-driven technique, it reduces unnecessary ambiguity in the choice of control variables and ad hoc decisions (Clarke, 2014). Using this approach, it is for example revealed that the R&D intensity of the licensee is considered a better control variable for licensor returns than its own R&D intensity. However, there also are potential downsides to it. The approach of overfitting the model rather than underfitting it is more likely to generate collinearity (Baum, 2012) or lead to the of use economically meaningless control variables (Woolridge, 2013). Maybe more importantly, the *GETS*-approach does not guarantee safety from misspecification, if the *GUM* itself is mis-specified (Campos et al., 2005). In other words, the final model generated by *genspec* largely depends on the variables that the *GUM* is specified with, and most importantly the quality of these variables.

In our case, very robust variables like firm sizes remain within the final model specification regardless of the *GUM*-specification. However, with default settings, *genspec* drops all variables with a p-value above 5.00%, which means that, theoretically, variables that might gain significance in later hypothesis tests may be omitted. This significance threshold can be difficult to achieve when investigating determinants of licensing returns, given that most explanatory variables generally explain little of the variation found in abnormal returns. Although the *GETS*-approach is generally appropriate for all types of regression analyses (Clarke, 2014), it may not be fine-tuned towards our type of study. Therefore, we decide to include R&D intensity and liquidity as controls for both partners, despite being omitted in the final specification of the *GETS*-approach. Including insignificant variables does not violate the OLS assumption of a zero-conditional mean and, therefore, OLS estimates should still be unbiased and robust although more imprecise (Baum, 2012). As we will later see in the

discussion of our results, for some sub-samples, aforementioned manually added controls seem to be highly meaningful and significant. Control variables are summarized in Table 9.

Table 9: Control Variables

Control Variable	Licensor Returns	Licensee Returns
Licensor: Firm Size	**x**	**x**
Licensee: Firm Size	**x**	**x**
Licensor: Firm Size Squared	-	-
Licensee: Firm Size Squared	-	-
Licensor: R&D Intensity	**(x)**	-
Licensee: R&D Intensity	**x**	**(x)**
Licensor: Liquidity	**(x)**	-
Licensee: Liquidity	-	**(x)**

6.3 EMPIRICAL CONSIDERATIONS

Lastly, we wish to address other empirical considerations that could influence our results. We mainly base our considerations on the so-called Gauss-Markov assumptions, one of which for example states that linear OLS regression models are a linear function of their individual explanatory variables (Gelman and Hill, 2006; Woolridge, 2013). We first use the *Stata command avplots* to check whether our sample is skewed by outliers. We use the command to regress aforementioned independent control variables against the dependent abnormal return variables and create scatter plots based on the results. Based on visual inspection, extreme outliers are identified. We prefer not to exclude observations based on pre-defined criteria as these extreme observations are not measurement errors per se but examples of extreme value creation or appropriation. Nonetheless, they could skew our results. We test whether the removal of outliers based on a Cook's distance criterion (Cook, 1977) improves the behavior of the residuals but find that this is not the case. This is supported by the fact that heterogeneity in residuals mainly stems from large firms with low abnormal returns.

An assumption in OLS regressions is homoscedasticity; meaning that residuals show a constant variance (Wooldridge, 2013). We test for heteroscedasticity using the *Stata command imtest*. Heteroscedasticity warrants the use of robust standard errors. In many cases however, issues arising from heteroscedasticity are minor (Gelman and Hill, 2006) and OLS estimates are still

likely to be unbiased (Woolridge, 2013). Normality tests for skewness and kurtosis tests are also included in *imtest*, but we acknowledge that they have little importance for linearity and unbiasedness considerations (Gelman and Hill, 2006; Wooldridge, 2013).

Furthermore, multicollinearity, meaning near-perfect linear correlation between independent variables, could cause estimates of regression coefficients to become unstable (Wooldridge, 2013). We use the *Stata command vif* to compute variance inflation factors (VIFs). Values above ten warrant investigation (Wooldridge, 2013). We test for potential omitted variable bias with the *Ramsey Regression Error Specification Test*, which tests if non-linear combinations of dependent variables have an influence on the independent variable (Woolridge, 2013). This would suggest that the assumption of a zero-conditional mean is not satisfied and that the model has omitted variables, which distorts inferences (Wooldridge, 2013).

For licensor returns, we find that the *Ramsey RESET* suggests an omitted variable bias unless an interaction term between both alliance partners' firm sizes is included in the specification (see Table 10). From a theoretical standpoint, it is not exactly clear why the marginal effect of licensor firm size on licensor returns should depend on the licensee's firm size. It could suggest an embedded ability to create value for the licensor's shareholders. This issue is however not observed in sub-samples. Although we argue that the inclusion of independent variables should be dictated by theoretical reasoning, the interaction term simply seems to be effective in solving non-linearity issues. It is highly statistically significant; thus, its exclusion leaves the model underfitted and leads to instable regression coefficients. Naturally, it introduces collinearity to the regression model (see Table 11). The mean VIF of 4.28 however does not warrant investigation, nor do individual VIFs, given that all are below 10. Testing for heteroscedasticity does not warrant the use of robust standard errors either (see Table 12). Thus, we can solve the linearity issue suggested by the *Ramsey RESET*, at the expense of increased collinearity, which

stands lower in the Gauss-Markov pecking order (Woolridge, 2013). Lastly, we find no reason to exclude any observation based on visual inspection.

Table 10: Ramsey Regression Specification Error Tests (Licensor)

	All Licensors	**All Licensors**	**Large Licensors**	**SME Licensors**
Interaction: Firm Size	NO	YES	NO	NO
F-value	7.33	2.29	2.69	1.60
Prob. > F-value	0.0010	0.0770	0.0459	0.1869
Omitted Variable Bias	**YES**	**NO**	**YES**	**NO**

Table 11: Variable Inflation Factors (Licensor)

	All Licensors	**Large Licensors**	**SME Licensors**
	VIF	VIF	VIF
Licensor: Firm Size	6.49	1.24	1.17
Licensee: Firm Size	6.21	1.45	1.14
Interaction: Firm Size	8.76	-	-
Licensor: R&D Intensity	1.31	1.16	1.09
Licensee: R&D Intensity	1.29	1.44	1.14
Liquidity	1.60	1.27	1.16
Mean VIF	**4.28**	**1.31**	**1.56**

Table 12: Heteroscedasticity Tests (Licensor)

	All Licensors			**Large Licensors**			**SME Licensors**		
	chi2	df	p	chi2	df	p	chi2	df	p
Heteroscedasticity	29.91	26	0.2714	108.72	20	0.000	17.02	20	0.651
Skewness	8.77	6	0.1869	17.30	5	0.004	5.66	5	0.340
Kurtosis	1.20	1	0.2733	3.67	1	0.055	1.20	1	0.273
Total	**39.88**	**33**	**0.1907**	**129.69**	**26**	**0.000**	**1.56**	**26**	**0.5824**

For licensee returns, we encounter opposite issues compared to licensors' returns. Residuals are generally more heteroscedastic (see Table 15), which warrants the use of robust standard errors, and we suspect that this is caused by the fact that our sample of licensees is generally skewed towards large firms, which boast lower and less explainable abnormal returns. On the other hand, the *Ramsey RESET* strongly rejects a potential omitted variable bias (see Table 13). An interaction term between firm sizes instead aggravates the model specification. We also notice that variable inflation factors do not warrant investigation (see Table 14).

Table 13: Ramsey Regression Specification Error Tests (Licensee)

	All Licensees	**All Licensees**	**Large Licensees**	**SME Licensees**
Interaction: Firm Size	NO	YES	NO	NO
F-value	1.38	2.29	2.61	0.49
Prob. > F-value	0.2477	0.0769	0.0505	0.6869
Omitted Variable Bias	**NO**	**NO**	**NO**	**NO**

Table 14: Variable Inflation Factors (Licensee)

	All Licensees	**Large Licensees**	**SME Licensees**
	VIF	VIF	VIF
Licensor: Firm Size	1.05	1.01	1.05
Licensee: Firm Size	2.14	1.29	1.29
R&D Intensity	1.27	1.24	1.11
Liquidity	2.20	1.41	1.31
Mean VIF	**1.66**	**1.24**	**1.19**

Table 15: Heteroscedasticity Tests (Licensee)

	All Licensees			**Large Licensees**			**SME Licensees**		
	chi2	df	p	chi2	df	p	chi2	df	p
Heteroscedasticity	49.23	14	0.000	27.39	14	0.017	17.08	14	0.252
Skewness	11.65	4	0.020	7.11	4	0.130	5.89	4	0.208
Kurtosis	1.36	1	0.244	1.91	1	0.167	1.30	1	0.254
Total	**62.23**	**19**	**0.000**	**36.41**	**19**	**0.009**	**24.27**	**19**	**0.185**

Nevertheless, given that most prior research has been done related to technology exchanges and alliances between small biotechnology and large pharmaceutical firms (Lerner and Merges, 1998; Lerner et al., 2003; Stuart et al., 1999; Nicholson et al., 2005; Higgins, 2007; Adegbesan and Higgins, 2010), our expansion beyond this setting could introduce a heterogeneity issue requiring consideration. By focusing on the pharmaceutical industry, we remove heterogeneity on an industry-specific level. However, research generally suggests that firm effects have greater determinacy than industry effects in explaining the performance of a given firm (Fernández et al., 2019). Therefore, we argue that determinants of value creation and value appropriation might not be the same for smaller firms as they are for large firms just because they belong to the same industry. The business models of large, multinational firms and small, research-intensive firms differ vastly—the latter being highly dependent on external financing and being unsure of when or how revenues are generated (Lazonick and Tulum, 2011). In addition to controlling for firm sizes, the robustness of our results can be assessed by conducting regressions for different firm size categories. This allows us to control for sample biases that could drive inferences made on the total sample. More importantly, we are also able to make an academic contribution by nuancing and expanding on the licensing setting in consistency with observed trends in the licensing market of drugs (Gassmann et al., 2016). It

is important to be aware that this could enable cherry picking. Arguably, determinants of value creation and appropriation are most valuable when they are robust across firm sizes.

The sub-samples we use are based on previously created market index cluster of small, medium, and large firms. However, since dividing the sample reduces the number of observations in exchange for reduced heterogeneity, too granular sub-samples could potentially reduce the value of inferences drawn from these sub-samples. A distinction between micro-, small- and medium-sized enterprises (SMEs) and large firms has been recognized in the pharmaceutical industry. The *European Medicines Agency* (*EMA*) is an EU regulatory agency with a similar role to the *FDA* in the US. In 2005, it created a SME-office in order to "address the unique needs of micro-, small- and medium-sized enterprises (SME)" (EMA, 2020).[10] A similar service from the *FDA* has a conceptual cut-off between small and large firms (FDA, 2020). Walter (2012) separates his sample by the median between large firms and small firms. However, it is important to at least acknowledge the existence of medium-sized firms, which have their own idiosyncrasies (Drucker, 1999). O'Connell et al. (2014) differentiate between large firms and SME firms, as they possess different asset bases as well as different strategic goals in licensing. This distinction is also more consistent with the notion of *Big Pharma* and essentially everything else. As such, we decide to differentiate the sample between SME and large firms to control for potential sample biases.

Splitting the sample in this way also provides several empirical benefits. Firstly, as firm size categories between licensor and licensee are symmetric to each other, returns as well as determinants can easily be compared across firm size categories. This is important, considering the notion that value creation and value appropriation are not independent from each other (Higgins and Adegbesan, 2010). The robustness of hypotheses can be tested by investigating

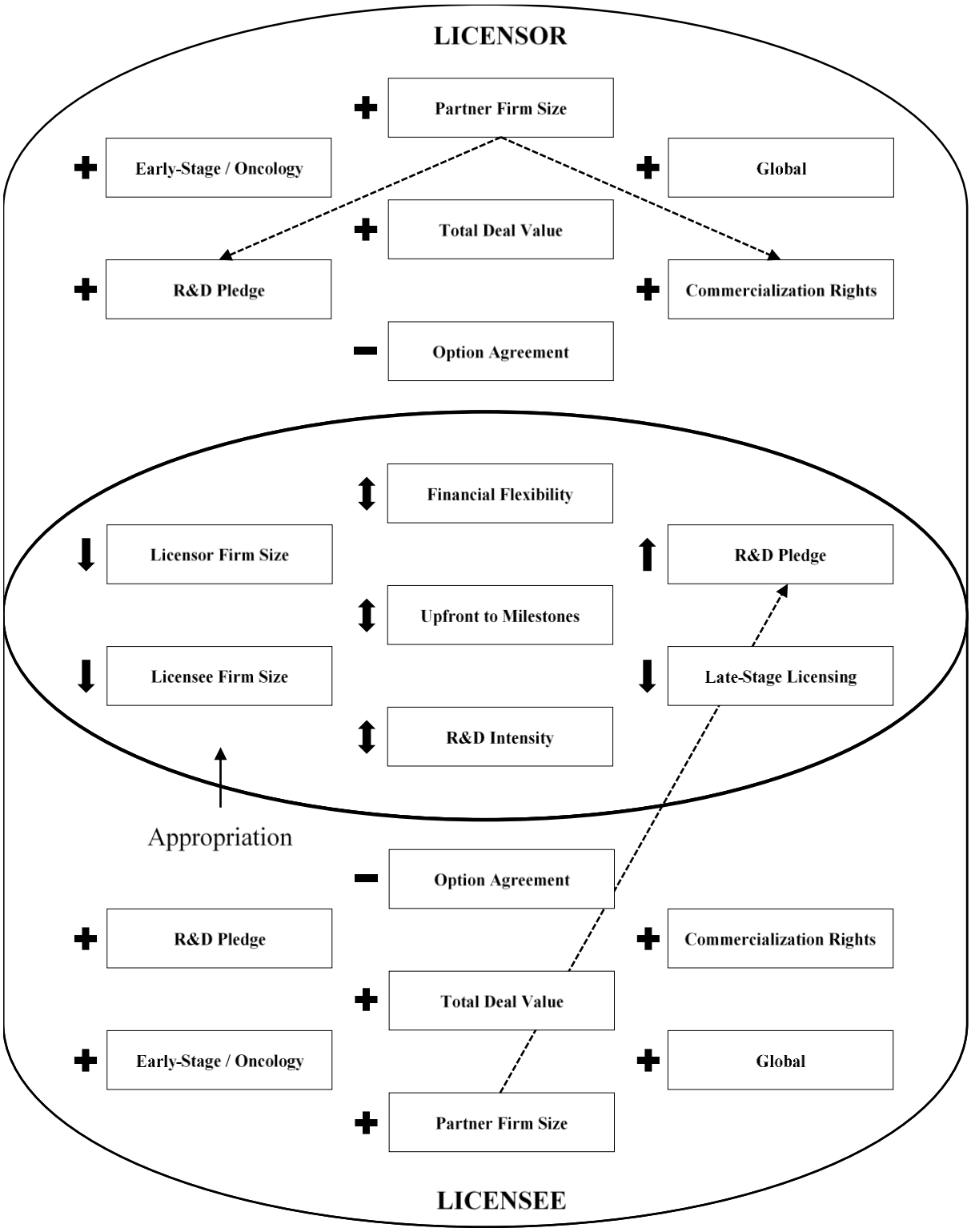
[10] The SME status provided by the *EMA* is based on the following two criterions: (1) fewer than 250 employees; and (2) either an annual turnover of not more than EUR 50 million or an annual balance-sheet total of not more than EUR 43 EUR (EMA, 2020).

returns on both sides of the licensing deal relative to their predictions. Secondly, the omitted variable bias for licensor returns can be circumvented by such a separation, as the null hypothesis in *Ramsey RESETs* does not get rejected, or at least not as strongly as before for large licensors (see Table 10). It means that an interaction term between firm sizes is not warranted anymore. Thirdly, it is noted that it improves test statistics for multicollinearity. We notice that residuals for large firms appear to be less well-behaved than residuals for SME firms (see Tables 10 to 15).

7. EMPIRICAL RESULTS

In this chapter, we summarize the results of our event study. We first illustrate average cumulative abnormal returns we find and their statistical significance across different combinations of firm sizes. We further investigate the robustness of these results based on slight modifications in our standard event study framework. Most importantly, we illustrate the evidence we find or do not find for and against our hypotheses (see Figure 11).

Figure 11: Potential Determinants of Value Creation and Appropriation [11]



[11] We allocate value creation mechanisms to either licensor or licensee (top and bottom area) based on our theoretical prediction. Value appropriation mechanisms are allocated in between. The sign to the left of a mechanism indicates the relation to predicted abnormal returns and / or the direction of value appropriation.

7.1 VALUE APPROPRIATION AND SCARCITY

As we anticipated based on prior empirical research (Anand and Khanna, 2000; Higgins, 2007; Walter, 2012; McConnell, 1985; Koh and Venkatraman, 1991; Das, Sen and Sengupta, 1997; Chan et al., 1997; Kale et al., 2002), we find evidence for positive returns from the announcement of licensing deals—both for the licensor and the licensee.

We find support for **Hypothesis 1a** with average cumulative abnormal returns of 4.41% for the licensor and 0.76% for the licensee—both with a significance on a 1%-level. Most notably, small, and medium-sized licensors register abnormal returns of 18.54% and 7.01% respectively whenever out-licensing to a large firm. In general, we acknowledge that the previously mentioned availability biases (i.e. all sample firms being listed and the potential that favorable information is over-represented) might skew the size of observed cumulative abnormal returns upwards. Nevertheless, drug licensing appears to create a value surplus, of which a majority befalls the licensor. As can be seen in Tables 16 and 17, licensors generally show higher abnormal returns for many combinations of firm size categories. This confines to our hypothesis that licensors appropriate value due to their scarcity. We relate exceptions to the fact that average cumulative abnormal returns for certain combinations of firm sizes are based on a small sample sizes and are statically insignificant. Furthermore, some of these exceptions might also indicate the presence of validation effects for the licensee.

Table 16: Cumulative Abnormal Returns (Licensor)

Licensor Returns	Small Licensors	Medium Licensors	Large Licensors	All Licensors
Small Licensees	**4.63***	0.76	–0.04	**1.02***
Medium Licensees	**5.06*****	**1.91*****	–0.35	**1.67*****
Large Licensees	**18.54*****	**7.01*****	0.46	**7.87*****
All Licensees	**10.20*****	**4.35*****	–0.02	**4.41*****

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

Table 17: Cumulative Licensee Returns (Licensee)

Licensee Returns	Small Licensees	Medium Licensees	Large Licensees	All Licensees
Small Licensors	–3.18	**1.43***	–0.04	–0.13
Medium Licensors	1.61	1.18	0.20	0.30
Large Licensors	**2.33***	**2.45*****	0.15	**1.43*****
All Licensors	**1.97***	**1.63*****	0.40	**0.76*****

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

7.1.1 ROBUSTNESS OF EVENT WINDOWS

Using an event window of [±2], we observe average cumulative abnormal of 4.33% for the licensor and of 0.71% for the licensee. The respective values for an event window of [±3] are 4.19% and 0.59%. Except the last value, which is statistically significant on a 5%-level, all other observed average returns are significant on a 1%-level. In general, magnitude and statistical significance are impacted slightly but not remarkably (see Tables 16 and 17). However, we notice that both deteriorate for licensee returns, when using a [±3] event window. Nonetheless, we reason that the choice of the event window does not impact results significantly—thus, that our empirical methodology is robust against the choice of event window. This is especially relevant as it also implies that the market is efficient in processing the information inherent in the announcement of the licensing deal.

Table 18: Alternative Event Windows (Licensor)

Licensor Returns	Small Licensors	Medium Licensors	Large Licensors	All Licensors
Event Window [±2]	**9.96*****	**4.18*****	0.13	**4.33*****
Event Window [±3]	**9.86*****	**3.89*****	0.19	**4.20*****

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

Table 19: Alternative Event Windows (Licensee)

Licensee Returns	Small Licensees	Medium Licensees	Large Licensees	All Licensees
Event Window [±2]	1.75	**1.50*****	0.09	**0.71*****
Event Window [±3]	1.94	**0.93***	0.03	**0.59****

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

7.1.2 ROBUSTNESS OF MARKET PORTFOLIOS

Our initial observations seem to remain stable when changing market portfolios—in each case with an [±1] event window. When using employees as an alternative firm size proxy to cluster our sample firms with, we observe average cumulative abnormal returns of 3.86% for the licensor and of 0.94% for the licensee. Results using all sample firms to construct a single market portfolio yield 4.44% for the licensor and 0.70% for the licensee. Lastly, using the *MSCI World Pharmaceuticals, Biotechnology and Life Sciences Index* as a market portfolio gives similar results at 4.48% and 0.73%. For an overview, see Tables 20 and 21.

Table 20: Alternative Market Portfolios (Licensor)

Licensor Returns	Small Licensors	Medium Licensors	Large Licensors	All Licensors
Employee-Indices	**7.39*****	**1.74*****	–0.12	**3.86*****
Sample-Index	**10.32*****	**4.39*****	–0.04	**4.44*****
MSCI World Pharma	**10.70*****	**4.23*****	–0.01	**4.48*****

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

Table 21: Alternative Market Portfolios (Licensee)

Licensee Returns	Small Licensees	Medium Licensees	Large Licensees	All Licensees
Employee-Indices	**2.95*****	**0.72*****	–0.04	**0.94*****
Sample-Index	1.75	**1.58*****	0.01	**0.70*****
MSCI World Pharma	**2.03****	**1.41*****	0.04	**0.73*****

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

Compared to our first mentioned results, it becomes evident that results using a sample-based index or the *MSCI World Pharmaceuticals, Biotechnology and Life Sciences Index* do not significantly deviate in magnitude. Statistical significance remains also broadly the same. When using indices created from employee-based firm size clusters however, results do in fact differ from those of our standard event study parameters.

For licensors, the magnitude of abnormal returns of small and medium firms is reduced. Overall average abnormal returns are consequently lower as well. We reckon that this is caused by the fact that we observe the number of employees for fewer observations than sales—535 less often to be exact and mostly for firms with close to zero sales. We furthermore notice that, while small firms make up 26% of the sample licensors using a sales-proxy, small firms make up

46% of the sample licensors using an employee-proxy. This fact likely skews average returns of the small firm licensor cluster towards the sample mean. We reckon that similarly medium-sized licensors—using a sales-proxy—are moved to the small firm licensor cluster, which then also explains why average returns for medium-sized licensors are smaller. We relate the overall change in average abnormal returns to the fact that we do not observe the number of employees for many firms with zero sales, which are generally likely to show significant abnormal returns. Our general observation that small licensors might benefit from validation effects remains evident, however. For licensees, we observe that average cumulative abnormal returns of small licensees significantly increase in magnitude as well as statistical significance. For medium-sized licensees, results are noticeably smaller but still significant on a 1%-level. We notice that this might be caused by the fact that—using an employee-proxy—the relative size of the small firm licensee cluster is smaller than using a sales-proxy. This likely causes the reverse effect of what we hypothesize to have caused the change in results for licensor returns.

7.2 BARGAINING PERSPECTIVES AND VALIDATION EFFECTS

For the licensor (see Table 22), OLS regressions confirm that its own firm size negatively impacts abnormal returns, possibly due to a potential loss of asymmetric dependency and bargaining ability (**Hypothesis 2a**). An increase in the firm size of the licensee, as expected, potentially mirrors a validation effect (**Hypothesis 2b**). Both effects are significant on a 1%-level. When separating between large licensors and SME licensors, it is noted that SME licensors seem to generate the effects that are observed for the whole sample, as firm size proxies are only significant for this sub-sample.

We find evidence against improved asset complementarity based on licensor R&D intensity (**Hypothesis 2c**). Opposite to what we expected, R&D intensity of the licensor appears to reduce its returns. This goes against the notions of comparative advantages (Aghion and Tirole, 1994; Grabowski and Kyle, 2012), as well as firms with higher R&D intensity being more

likely to develop more attractive technology (Cohen and Levinthal, 1990). As previously explained, we find that the R&D intensity of the licensee significantly improves licensor returns and that this effect is robust in most model specifications. The advantages of absorptive capacity for licensees are well researched but they also appear to be indicative for licensor returns. We argue that a R&D-intensive licensee might create a valuable R&D interface between the firms. Walter (2012) argues that R&D intensity enhances a firm's ability to identify the value of technologies. As such, the value of a valuable research project might be better recognized by a R&D-intensive licensee, which in return is willing to offer more value to the licensor. Thus, the R&D intensity of the licensee helps the licensor communicate the fair value of their project. Therefore, it seems to mitigate information asymmetries and be more of a value-creation mechanism, in similarity to partner firm size. This seems more plausible than the idea that the licensor can appropriate value based on the partner's R&D intensity, especially considering its unable to appropriate based on its own.

Lastly, we find weak support for **Hypothesis 2d**, as liquidity apparently improves the bargaining ability of licensors, as they can retain their scarcity premium. This effect is especially pronounced for SME licensors, which makes intuitive sense. However, observed effects lack statistical significance. Given that bargaining ability relates to the distribution of a residual value surplus, there generally just may not be much residual value left to be distributed based on bargaining ability. Moreover, as it seems unlikely that the liquidity of any firm is a value-creation determinant in the alliance, it can be expected to explicitly capture value appropriation. This could suggest a causality problem. If some variables can increase the size of the pie as well as determine its division simultaneously, this could inflate their economic properties and complicate inferences. Explicitly value-appropriating variables, however, might lack significance because they do not impact overall benefits created in the alliance.

Table 22: Bargaining Perspectives and Validation Effects (Licensor)

All / Large / SME Licensors	**Coef.**			**St. Err.**			**p-value**		
Licensor: Firm Size	0.156	-0.281	**-1.068**	0.235	0.273	**0.329**	0.506	0.304	**0.001*****
Licensee: Firm Size	**1.571**	0.060	**0.930**	**0.349**	0.047	**0.171**	**0.000*****	0.200	**0.000*****
Interaction: Firm Size	**-0.103**	-	-	**0.028**	-	-	**0.000*****	-	-
Licensor: R&D Intensity	-4.590	0.351	-6.116	3.293	1.493	4.090	0.164	0.814	0.135
Licensee: R&D Intensity	**3.302**	0.185	4.395	**1.710**	0.652	2.769	**0.054***	0.776	0.113
Liquidity	3.766	0.494	3.632	2.744	3.877	2.911	0.170	0.899	0.212
Constant	-3.741	3.207	4.392	3.666	3.674	4.683	0.308	0.383	0.348
Mean dependent var.	4.939	0.113	7.723	SD dependent var.			20.550	4.319	25.183
R-squared	0.079	0.014	0.047	Number of obs.			1375	503	872

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

For the licensee (see Table 23), we find that an increase in firm size negatively impacts returns on a 1%-level. This speaks against **Hypothesis 2a**, which predicts a positive coefficient due to superior asset complementarity. In accordance with **Hypothesis 2b**, we find weak support for a validation effect as returns positively correlate with the firm size of the licensing partner. For the full sample, it this effect is statistically insignificant. However, for SME licensees, it is significant on a 10%-level. This is consistent with the results from Table 17 where large licensors seemingly amplify validation effects for SME licensees.

We find no support for **Hypothesis 2c** and **2d**, which predicted a correlation of returns with R&D intensity and liquidity. Even for SME licensees, financial flexibility does not seem to impact returns. R&D intensity appears to be slightly more significant on a sub-sample level, albeit remaining statistically insignificant. Interestingly, the results show different coefficient signs when comparing sub-samples. R&D intensity is positively correlated with returns for large licensees, while being negatively correlated with returns for SME licensees. This pattern is consistent with that of the licensors, where R&D intensity has a negative impact if the firm is small and vice versa a positive impact if the firm is large. We find no explanation for these patterns based on the theoretical framework. Considering an inverse relationship between firm size and R&D intensity, we think that these effects are unlikely to be caused by firm size effects being attributed to R&D intensity. Effects related to R&D intensity might indicate the maturity of the firms or the lack of such and related value creation based on industry experience.

Table 23: Bargaining Perspectives and Validation Effects (Licensee)

All / Large / SME Licensees	Coef.			St. Err.			p-value		
Licensee: Firm Size	**-0.257**	0.020	**-0.266**	**0.080**	0.125	**0.148**	**0.001*****	0.873	**0.073***
Licensor: Firm Size	0.064	0.026	0.125	0.044	0.026	0.096	0.147	0.324	0.195
R&D Intensity	-0.487	1.188	-1.968	1.216	1.017	1.721	0.689	0.243	0.253
Liquidity	-0.018	0.903	-0.296	1.940	1.427	2.202	0.993	0.527	0.893
Constant	**3.253**	-1.039	**3.704**	**1.429**	1.936	**1.965**	**0.023****	0.592	**0.060***
Mean dependent var.	0.865	-0.065	2.250	SD dependent var.			8.751	3.637	12.958
R-squared	0.021	0.005	0.008	Number of obs.			1501	898	603

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

7.3 CONTRACTUAL DESIGN

For **Hypothesis 3a**, we find weak support that upfront payments are preferable to milestones in the payment structure for licensors (see Table 24). For large licensors, the coefficient is small in magnitude, however for SME licensors, we find the return differential between a pure-upfront deal against a pure-milestone deal to be 6.12%. This large magnitude is consistent with the notion that upfront payments are preferable for licensors as they reflect immediate cash infusions rather than future conditional payments (Higgins, 2007) and can be explained by the fact that SME firms are associated with more financially constraints (O'Connell et al., 2014).

Table 24: Contractual Design (Licensor)

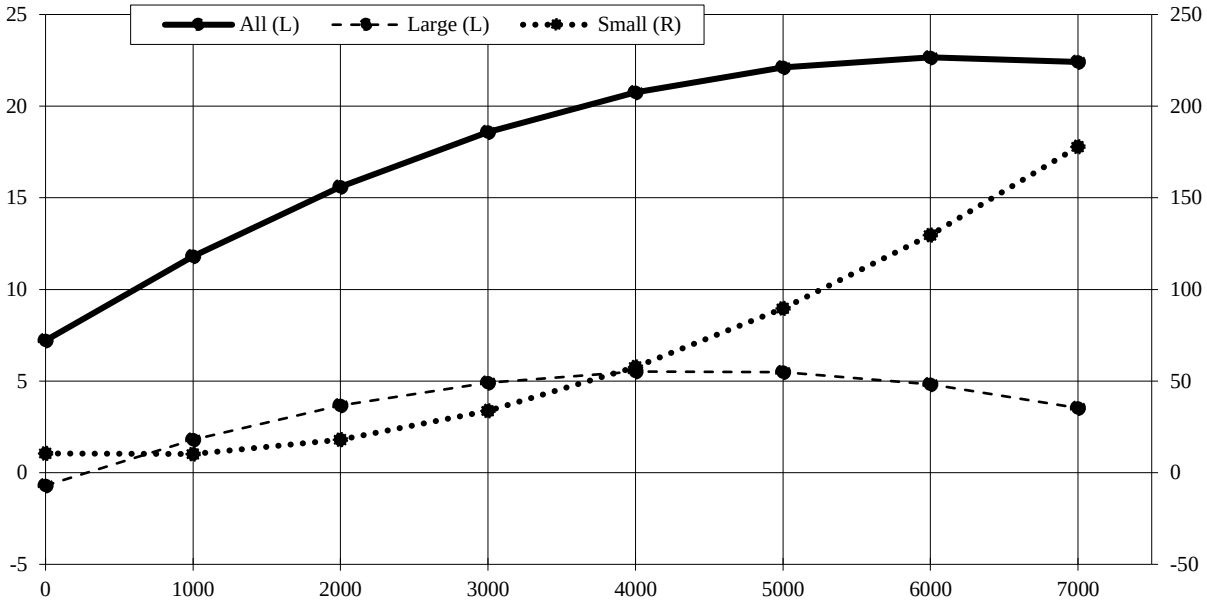
All / Large / SME Licensors	Coef.			St. Err.			p-value		
Licensor: Firm Size	0.065	-1.325	**-1.564**	0.575	1.135	**0.434**	0.910	0.248	**0.000*****
Licensee: Firm Size	**2.030**	-0.064	**1.055**	**0.599**	0.210	**0.301**	**0.001*****	0.760	**0.001*****
Interaction: Firm Size	**-0.139**	-	-	**0.057**	-	-	**0.015****	-	-
Licensor: R&D Intensity	**-12.894**	-1.631	**-17.484**	**4.530**	4.068	**5.771**	**0.005*****	0.690	**0.003*****
Licensee: R&D Intensity	8.421	-0.917	8.209	5.887	3.733	7.731	0.153	0.807	0.289
Liquidity	**10.624**	-1.883	**11.892**	**5.335**	13.345	**5.555**	**0.047****	0.888	**0.033****
Total Deal Value	-	**0.004**	-	-	**0.002**	-	-	**0.039****	-
Total Deal Value (Sq)	-	**0.000**	-	-	**0.000**	-	-	**0.081***	-
Total Deal Value (Log)	**1.812**	-	**2.978**	**0.943**	-	**1.316**	**0.056***	-	**0.024****
Upfront to Milestones	0.516	-0.188	6.118	0.914	0.121	4.262	0.572	0.126	0.152
Constant	-11.899	18.678	-6.108	10.628	17.274	9.782	0.264	0.284	0.533
Mean dependent var.	9.857	1.327	11.834	SD dependent var.			23.125	8.614	24.925
R-squared	0.145	0.135	0.138	Number of obs.			388	73	315

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

In accordance with **Hypothesis 3b**, we find that percentage increases in deal value impact licensor returns positively due to a potentially increased validation effect. The effect is significant on a 10%-level for all licensor returns, and a 5%-level for SME licensors. Thus, it appears that SME firms are driving a positive logarithmic effect that deal value has for the

whole sample. Surprisingly, the effect deal value has on the returns for large licensors appears to be much more non-logarithmic than for SME licensor returns, as well as highly concave (see Figure 12). A non-logarithmic effect of deal value on all and SME licensor returns is statistically insignificant, while it is significant for large licensor returns. Thus, it appears that a logarithmic interpretation of **Hypothesis 3b** only applies to SME licensors. For large licensors, both a linear and a quadratic interpretation of deal value are statistically significant on 5%- and 10%-significance levels, respectively. This suggests that the market response to the value of the deal is not increasing monotonously for large licensors.

Figure 12: Effects of Total Deal Value on Licensor Returns



Additionally, we notice that R&D intensity and financial strength of the licensor gain statistical significance when controlling for payment characteristics. As previously noted, the coefficient sign for R&D intensity goes against our predictions (**Hypothesis 2c**). However, we now find statistical support on a 5%-level that financial strength potentially improves the bargaining ability of the licensor (**Hypothesis 2d**), which is mostly driven by SME firms. Nonetheless, we further notice that the inclusion of contractual design considerations greatly reduces our sample size. Based on potential availability bias and thus over-representation of favourable

information, we find that average abnormal returns of this sub-sample are twice the sample average. Thus, conclusions regarding bargaining perspectives are not generalizable.

On the licensee side, we find no support for **Hypothesis 3a** for large licensees (see Table 25). For SME licensees, we however find strong support against it. It appears that the market reacts more positively to deals with relatively larger upfront payments. In theory, licensees should prefer milestones (Higgins; 2007; Crama et al., 2008). Crama et al. (2008) point out however that their contract design suggestions are based on a stylized model, and that it may be inappropriate to extrapolate their conclusions to contract situations where their assumptions do not apply. Based on O'Connell et al. (2014), deals with relatively large upfront payments could indicate the licensing of valuable drugs due to stronger licensor bargaining ability and thus send a positive signal to the market if the licensee can acquire control over it. If due diligence concludes that the drug is of high quality, then the licensee may be less reluctant to pay a large upfront payment. However, this does not explain why this effect is absent for large licensees. If large licensees face less financial constraints in the market of drug licensing (O'Connell et al., 2014), they should even more be indifferent between paying upfront and milestone payments. A plausible explanation for this discrepancy is that in-licensing is a larger relative-value-event for SME licensees than for large licensees. This could suggest that the upfront payment may have a significant signal value and therefore be a value creation determinant rather than an indication of value appropriation, in similarity to the deal value. Perhaps both explanations are valid, while the proxy in the form of stock returns is biased towards signals rather than contractual considerations.

Table 25: Contractual Design (Licensee)

All / Large / SME Licensees	Coef.			St. Err.			p-value		
Licensee: Firm Size	-0.135	0.156	-0.464	0.223	0.314	0.609	0.544	0.619	0.447
Licensor: Firm Size	0.105	0.053	0.115	0.080	0.058	0.264	0.193	0.366	0.664
R&D Intensity	0.065	-0.344	-7.189	2.729	1.872	8.450	0.981	0.854	0.397
Liquidity	4.618	3.323	5.126	5.467	2.307	7.947	0.399	0.151	0.520
Total Deal Value	0.002	0.000	0.046	0.002	0.000	0.031	0.191	0.409	0.143
Total Deal Value (Sq)	0.000	**0.000**	0.000	0.000	**0.000**	0.000	0.112	**0.037****	0.144
Total Deal Value (Log)	-	-	-	-	-	-	-	-	-
Upfront to Milestones	0.026	0.018	**3.021**	0.104	0.050	**1.304**	0.803	0.714	**0.023****
Constant	-0.547	-3.044	-2.847	2.833	4.950	5.331	0.847	0.539	0.594
Mean dependent var.	0.488	-0.142	2.210	SD dependent var.			10.479	3.479	19.377
R-squared	0.030	0.024	0.112	Number of obs.			407	298	109

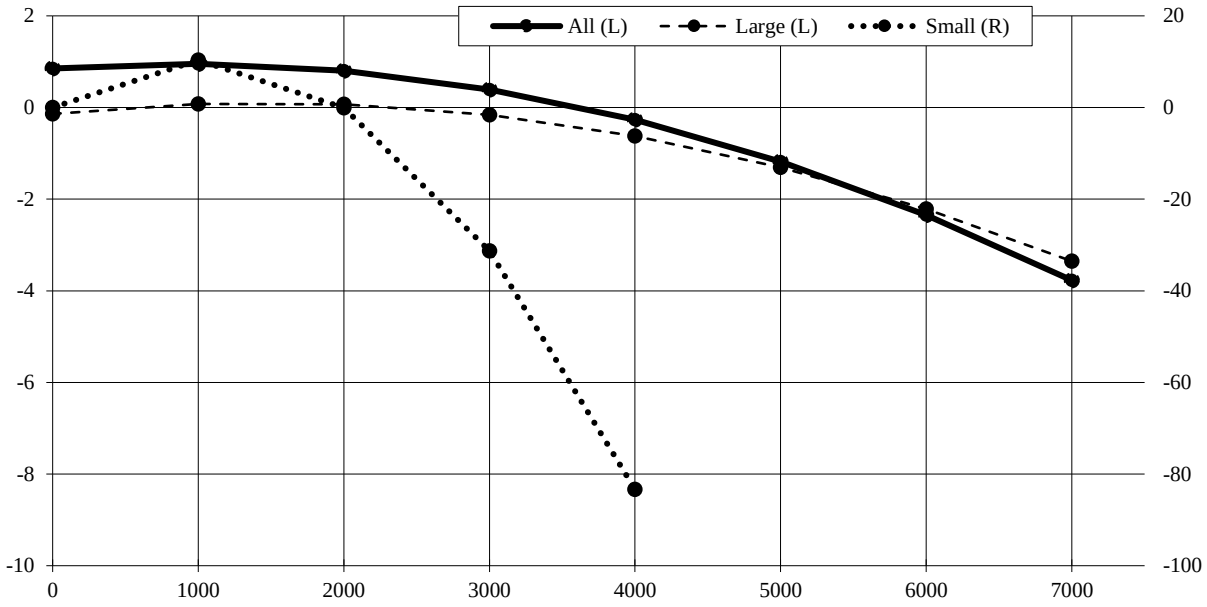
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Regarding **Hypothesis 3b**, we note that the effect deal value has on licensee returns is non-linear (see Figure 13), albeit insignificant in most cases. Using a quadratic function of deal value improves inferences made for licensee returns, which partially invalidates our linearly stated hypothesis. Interestingly, deal value now appears to be a highly concave function for SME firms, which suggests that the concavity of the effect of deal value on returns, for licensors and licensees, is not determined by firm size given that large licensors note large concavity.

For large licensee returns, the negative quadratic effect that deal value generates is statistically significant on the 5%-level. This is consistent with evidence that large licensees generally pay more than SME licensees when in-licensing, but not necessarily that these drugs reflect high quality (O'Connell et al., 2014), given that the market shows aversion towards deals with higher deal values. For SME licensees, fitted returns explained by deal value are positive between zero and USD 2 billion and highest at around USD 1 billion. The marginal effect is considerably more concave than for large licensees. A straight-forward explanation for this could be that SME licensees rarely engage in licensing deals with deal values significantly above USD 1 billion as they lack the financial resources to do so. Thus, predictions of abnormal announcement returns significantly above USD 1 billion are fictious. Nevertheless, the results are intriguing, as the marginal effect of deal value on SME licensor returns is convex, while concave for the other three sub-samples.

The results are consistent with the notion that high value deals reflect high quality drugs (O'Connell et al., 2014), and are generally suggestive of a scarcity premium that the licensor possesses. The NPV propositions of these in-licensed high-profile drugs may be weak after their price tag has been taken into consideration despite having attractive therapeutic profiles. Moreover, the deal value does not take development risk into account. Unfortunately, this study is unable to control for licensee bidding competition on the market prior to the announcement, which has increased in recent years (Gassmann et al., 2016).

Figure 13: Effects of Total Deal Value on Licensee Returns



7.4 INTRICACIES IN CONTRACTUAL DESIGN

For the licensor (see Table 26), we find weak statistical support for our hypothesis that a *call-back option* reduces validation effects (**Hypothesis 4a**). For the whole sample, the coefficient is negative as predicted. However, in fact, for large licensors, *call-back options* positively influence returns on a 5%-significance level. In this model specification, the marginal impact of *call-back option* is 3.61% relative to a constant of 0.48% and a sub-sample mean of 0.23%. However, generalizability is weak given the low number of observations of *call-back options* for large licensors. Nonetheless, option agreements appear to generate value for large licensors, given the large economic magnitude they have on otherwise close-to-zero returns. Given that

this effect is only noted for large licensors, this could suggest that including *call-back options* to mitigate the risk of underestimating the potential of the drug (Gassmann et al., 2016) could be beneficial if the licensor would not benefit from validation effects anyhow.

Table 26: Intricacies of Contractual Design 1/2 (Licensor)

All / Large / SME Licensors	**Coef.**			**St. Err.**			**p-value**		
Licensor: Firm Size	0.472	-0.244	**-1.079**	0.377	0.459	0.399	0.211	0.595	**0.007*****
Licensee: Firm Size	**2.124**	**0.174**	**1.144**	**0.477**	**0.094**	0.234	**0.000*****	**0.067***	**0.000*****
Interaction: Firm Size	**-0.137**	-	-	**0.039**	-	-	**0.000*****	-	-
Licensor: R&D Intensity	**-9.282**	-0.060	**-11.733**	**3.514**	1.957	4.350	**0.008*****	0.975	**0.007*****
Licensee: R&D Intensity	4.701	**2.515**	4.037	3.063	**1.283**	4.761	0.125	**0.051***	0.397
Liquidity	**8.583**	4.855	**8.741**	**4.322**	5.519	4.662	**0.047****	0.380	**0.061***
Option Agreement	-3.168	**3.607**	-4.333	2.921	**1.482**	3.409	0.279	**0.016****	0.204
Global	**4.709**	-0.387	**7.403**	**1.608**	0.813	2.414	**0.004*****	0.634	**0.002*****
Constant	-10.036	0.481	1.719	6.168	6.121	6.216	0.104	0.937	0.782
Mean dependent var.	6.116	0.225	8.964	SD dependent var.			19.378	5.100	22.802
R-squared	0.149	0.053	0.113	Number of obs.			669	218	451

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

When it comes to global agreements, they appear to have a large positive impact on SME licensor returns, which is significant on a 1%-level and is consistent with the prediction that global agreements generate a strong validation signal for the licensor. The effect is not observed for large licensors, which supports a validation theory. Moreover, the results dispute the notion that licensors may maximize benefits by granting exclusive rights for individual geographic regions to different licensees (Mendes, 2000). Therefore, we argue that the results are both empirically and theoretically meaningful.

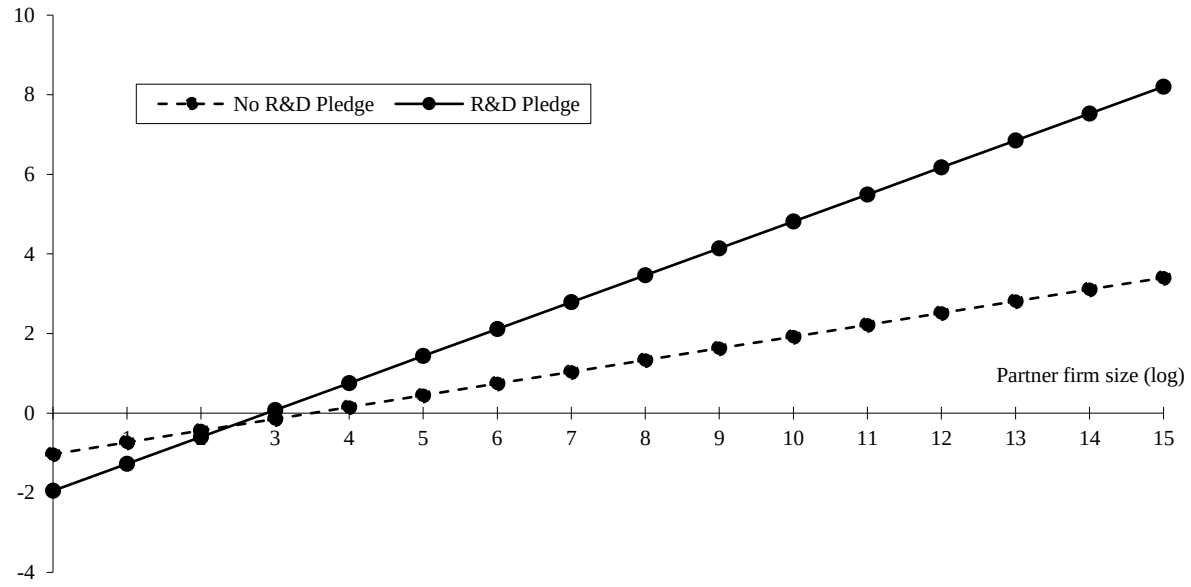
Table 27: Intricacies of Contractual Design 2/2 (Licensor)

All / Large / SME Licensors	**Coef.**			**St. Err.**			**p-value**		
Licensor: Firm Size	0.106	-0.241	**-1.140**	0.231	0.255	**0.311**	0.648	0.345	**0.000*****
Licensee: Firm Size	0.839	-0.008	-0.240	0.518	0.126	0.508	0.105	0.949	0.636
Interaction: Firm Size	**-0.096**	-	-	0.029	-	-	**0.001*****	-	-
Licensor: R&D Intensity	**-5.724**	0.193	**-7.642**	2.999	1.444	3.591	**0.057***	0.894	**0.034****
Licensee: R&D Intensity	2.706	0.298	3.648	2.054	0.667	3.283	0.188	0.655	0.267
Liquidity	3.579	0.655	3.409	2.741	3.850	2.920	0.192	0.865	0.243
R&D Pledge	-0.920	0.073	-2.927	1.722	1.187	3.176	0.593	0.951	0.357
Interaction: R&D Pledge	**0.381**	0.027	**0.713**	0.188	0.118	0.318	**0.042****	0.822	**0.025****
Commercialization Rights	-1.702	-0.029	-2.920	1.425	0.565	2.767	0.233	0.959	0.292
Interaction: Com. Rights	0.442	0.076	0.662	0.270	0.078	0.431	0.103	0.334	0.125
Constant	-0.175	2.582	**11.220**	3.179	3.933	4.336	0.956	0.512	**0.010****
Mean dependent var.	4.939	0.113	7.723	SD dependent var.			20.550	4.319	25.183
R-squared	0.086	0.020	0.059	Number of obs.			1375	503	872

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

Similarly, we find evidence (see Table 27) for our hypothesis that the positive validation signal of validation that a R&D pledge sends is amplified by the size of the licensee (**Hypothesis 4b**). The slope is statistically significant on the 5%-level (see Figure 14). We furthermore find a similar relationship for commercialization rights with a positive slope, which is significant slightly above a 10%-level (**Hypothesis 4c**). Both results seem to be driven by SME firms, which again strengthens a validation theory. The strong support for **Hypothesis 4b** could also indicate value appropriation stemming from the moral hazard issue facing the licensee when financing R&D (Lerner and Merges, 1998). As large licensees have larger asset bases than financially constraint SME licensees (O'Connell et al., 2014), the market might believe that the licensor is able to siphon value from large firms. Another, perhaps more straight-forward interpretation is that R&D pledges in licensing are valuable when the partner firm has potentially unrestricted resources to pledge, which could indicate a more successful outcome of the licensing agreement.

Figure 14: Marginal Effects of R&D Pledges and Partner Firm Size on Licensor Returns



For licensees (see Table 28), we find support that option agreements create a negative signal for large ones (**Hypothesis 4a**). No support is found for SME licensees. Given the positive impact on large licensor returns, results are consistent with the idea that *call-back options* imply licensor bargaining power (Reepmeyer, 2006). Nevertheless, although the marginal effect of option agreements is negative for SME licensees, average predicted returns are still positive. An SME licensee may be willing to accept the inclusion of a *call-back option* if it allows their capabilities to be validated by a large firm. Thus, they may be willing to accept a discount which is consistent with the findings of Nicholson et al. (2005). Generally, option agreements are considered to demonstrate new partnership models for value creation (Gassmann et al., 2016). However, the results question why large licensees should enter licensing contracts in which the licensor is able to retrieve the drug in case it proves to be a success. Naturally, the real option may be costly to trigger, which will generate income to the licensee, but the market seems to show aversion when the upside is in some sense capped for the licensee. When the validation effect is absent, deals with *call-back options* appear to reflect value appropriation towards larger licensors with bargaining power. Entering these more one-sided agreements could suggest a desperation amongst large licensees to gain exposure to technologies they lack, as they typically prefer licensing deals in which they gain full control over the drug (Reepmeyer, 2006). Whether option agreements are value-creating or -appropriating is unclear, given that both a commercial underestimation and moral hazard issue are ex post in nature. At the same time, without the *call-back option*, many large pharmaceutical licensors might otherwise restrain from out-licensing (Reepmeyer, 2006). Therefore, we argue that these agreements are mainly value-creating, as no licensing agreement would exist in the first place.

Table 28: Intricacies in Contractual Design 1/2 (Licensee)

All / Large / SME Licensees	Coef.			St. Err.			p-value		
Licensee: Firm Size	**-0.256**	-0.185	-0.228	**0.146**	0.201	0.269	**0.080***	0.357	0.397
Licensor: Firm Size	0.082	0.033	0.223	0.065	0.043	0.162	0.212	0.446	0.169
R&D Intensity	-0.977	1.477	-2.500	2.149	1.616	3.449	0.649	0.361	0.469
Liquidity	-0.292	2.501	-1.238	2.908	1.970	3.532	0.920	0.205	0.726
Option Agreement	**-0.903**	**-0.827**	-1.723	**0.503**	**0.431**	1.325	**0.073***	**0.055***	0.195
Global	0.387	**0.899**	-0.808	0.698	**0.447**	1.872	0.580	**0.045****	0.667
Constant	3.185	1.087	3.593	2.470	2.889	3.912	0.198	0.707	0.359
Mean dependent var.	0.759	-0.064	2.220	SD dependent var.			7.960	4.497	11.704
R-squared	0.022	0.022	0.015	Number of obs.			705	451	254

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

Regarding global commercialization agreements**,** we find statistically significant support for the hypothesis that they should positively influence licensee returns, given superior asset complementarity (**Hypothesis 4a**). Statistical significance is only noted for large licensees, which suggests that the hypothesis should have been specified only towards licensees that possess scale and therefore greater ability to commercialize drugs globally. Arguably, if global agreements allow the licensee to leverage its scale, then they should benefit large licensees the most. As SME licensees have less economies of scale to exploit, global agreements do not seem to be determinant of value creation for them. Thus, global agreements seem to be a win/win proposition for SME licensors and large licensees, where the former primarily gains a strong validation effect, while the latter can leverage its scale.

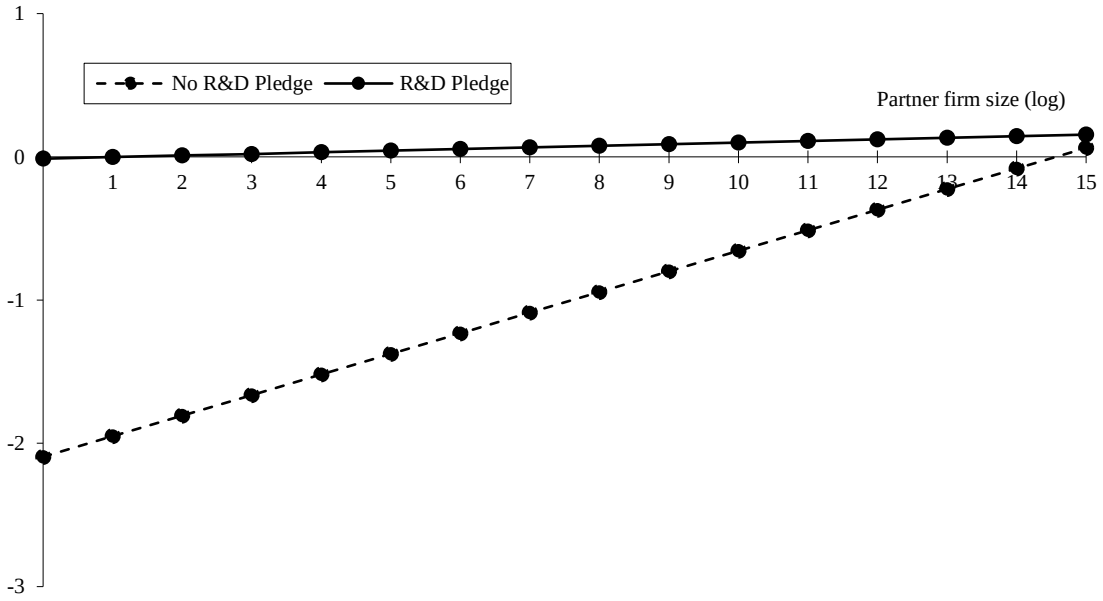
Table 29: Intricacies in Contractual Design 2/2 (Licensee)

All / Large / SME Licensees	Coef.			St. Err.			p-value		
Licensee: Firm Size	**-0.262**	-0.037	**-0.269**	**0.081**	0.135	**0.148**	**0.001*****	0.782	**0.070***
Licensor: Firm Size	0.169	**0.144**	0.217	0.126	**0.077**	0.269	0.180	**0.064***	0.422
R&D Intensity	-0.514	0.649	-1.373	1.365	0.921	1.987	0.707	0.482	0.490
Liquidity	-0.035	0.664	-0.286	1.926	1.439	2.181	0.985	0.644	0.896
R&D Pledge	1.308	**2.081**	0.225	1.286	**0.870**	2.749	0.309	**0.017****	0.935
Interaction: R&D Pledge	-0.127	-0.133	-0.115	0.137	0.082	0.287	0.355	0.106	0.688
Commercialization Rights	0.169	-0.148	0.588	0.486	0.225	1.112	0.728	0.511	0.597
Constant	2.089	-1.741	2.783	1.845	1.997	3.156	0.258	0.384	0.378
Mean dependent var.	0.865	-0.065	2.250	SD dependent var.			8.751	3.637	12.958
R-squared	0.022	0.016	0.010	Number of obs.			1501	898	603

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

Hypotheses 4b provides further support for the decision to split the licensee sample into two sub-samples (see Table 29). For large firms, the intercept of R&D pledge is almost statistically significant on the 10%-level, while the interaction term between R&D pledges and partner firm size has a significance close to an 1%-level. In contrast to other relationships, both the intercept and slope are positive (see Figure 14). However, the slope is very small compared to deals with no R&D pledge, which is believed to illustrate the moral hazard issue facing licensees. The larger the partner firm is, the likelier it is to possess a significant amount of existing R&D projects. It should therefore be able to attract financing more easily. As such, the rationale for R&D pledges weakens, which is supported by the stagnating effect R&D pledges have across partner firm sizes. This relationship is only observed for large licensees. Furthermore, we find no support that a transfer of commercialization rights positively influences licensee returns (**Hypothesis 4c**). Although a transfer of global commercialization rights seems to create value when compared against transfer of rights for specific geographical regions, on neither side, commercialization rights themselves appear to be a determinant of value creation.

Figure 15: Marginal Effects of R&D Pledges and Partner Firm Size on Licensee Returns



7.5 INFORMATION ASYMMETRIES

For licensors (see Table 30), we find no support of a stronger validation signal being generated from early-stage development deals (**Hypothesis 3a**). However, it appears that out-licensing *Phase III* drug candidates has a highly negative impact on licensor returns. Most surprisingly, this effect is pronounced for SME licensors but not large ones. This can be related to the large return differential between the two sub-samples of 8.1% and –0.02% respectively. However, it is reasonable to assume that late-stage licensing should be more beneficial for smaller firms than large firms, given that they do not possess enough resources to commercialize the drug, which would be consistent with recommendations in the *Licensing Management Matrix*. The absence of a validation effect could be a plausible explanation to the results. If information asymmetries are less pronounced in late-stage development (Banerjee and Siebert, 2017), then deals made in that stage will note lower returns compared to deals made in the *Preclinical Phase, Phase I* and *Phase II*. However, this explanation is weakened by the fact that unreported regressions show that licensing deals for fully developed drugs do not exhibit a similarly negative or statistically significant marginal effect.

Table 30: Information Asymmetries (Licensor)

All / Large / SME Licensors	**Coef.**			**St. Err.**			**p-value**		
Licensor: Firm Size	0.276	-0.099	**-1.029**	0.276	0.384	0.353	0.366	0.797	**0.004*****
Licensee: Firm Size	**1.593**	0.170	**0.796**	1.593	0.106	0.207	**0.000*****	0.109	**0.000*****
Interaction: Firm Size	**-0.105**	-	-	-0.105	-	-	**0.000*****	-	-
Licensor: R&D Intensity	-3.643	-0.690	-4.000	-3.643	1.581	3.856	0.231	0.663	0.300
Licensee: R&D Intensity	3.060	0.633	3.427	3.060	1.098	3.852	0.196	0.565	0.374
Liquidity	5.276	3.826	5.076	5.276	5.016	3.765	0.133	0.446	0.178
Preclinical	1.547	-0.044	1.791	1.547	0.656	2.059	0.293	0.946	0.385
Phase III	**-3.067**	-0.192	**-4.593**	-3.067	0.748	2.211	**0.020****	0.798	**0.038****
Immuno-Oncology	2.157	-1.361	2.395	2.157	0.937	5.511	0.359	0.147	0.664
Interaction: I-Oncology	-0.336	0.186	-0.459	-0.336	0.164	0.562	0.314	0.258	0.415
Cancer	-1.385	**2.768**	-4.649	-1.385	1.054	4.296	0.574	**0.009*****	0.280
Interaction: Cancer	0.248	**0.178**	0.567	0.248	0.178	0.482	0.453	**0.055***	0.241
Constant	-5.629	5.154	4.373	-5.629	5.154	5.004	0.218	0.908	0.383
Mean dependent var.	5.003	-0.016	8.090	SD dependent var.			18.257	4.549	22.382
R-squared	0.122	0.032	0.083	Number of obs.			919	350	569

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

Given that we note the reverse relationship for large licensees in *Phase III*, this seems to suggest a setting in which the licensee can appropriate value from the licensing deal at the expense of smaller licensors. For large licensees (see Table 31), in-licensing in this stage is associated with a positive coefficient with statistical significance on the 5%-level. As large licensees hold comparative advantages for licensing in late-stage drugs, the market appears to view such deals positively. In relation to average sub-sample return means, the marginal effect has a relatively large economic magnitude.

Naturally, just because the coefficient is negative in *Phase III* for licensors and positive for licensees, this does not necessarily indicate value appropriation from one partner to the other. We acknowledge that the evidence is correlational rather than causal. Therefore, the results do not necessarily dispute the notion that licensors hold bargaining power over licensees even for late-stage licensing (Higgins, 2007; Higgins and Adegbesan, 2011; Lerner et al., 2003). As information asymmetries are less pronounced in late-stage licensing and the motive of the licensor is often related to funding issues (Banerjee and Siebert, 2017), we suggest that *Phase III* licensing could lead to value appropriation by the licensee in comparison to the mutual value creation in early-stage deals. Unfortunately, the results for early-stage licensing are inconclusive and therefore unable to support or discard such an explanation.

There is also another plausible explanation: Market expectations. In the pharmaceutical industry, it has been found that the impact on firm value is severe when expectations about new products are not matched (Sharma and Lacey, 2004). An important consideration regarding our event study framework is that it is difficult to control for market expectations. For earnings announcements, this for example can be done by comparing earnings to expected earnings and calculating the earnings surprise (Bernard and Thomas, 1990). In pharmaceutical M&A, Higgins and Rodriguez (2006) find that each acquiring firm had on average four alliances with the target firm prior to the acquisition. Prior contact with a target firm through alliances can

serve to reduce information asymmetries (Anand and Khanna, 2000). Considering this, *Phase III* licensing can be considered a highly value-relevant event for SME firms. Suppose that a licensor possesses few R&D projects and enters a late-stage licensing agreement for its flagship drug candidate. As the licensor does not have the resource base to commercialize the drug themselves (Banerjee and Siebert, 2017), the market expects either the licensing of the drug or the acquisition of the licensor at a most likely above-market price per share. Thus, as the market at least partially expects an acquisition of the licensor, the announcement of the licensing deal may disappoint investors, similar to a negative earnings surprise. As such, the opportunity cost for late-stage out-licensing may be much higher due to heightened market expectations.

Table 31: Information Asymmetries (Licensee)

All / Large / SME Licensees	**Coef.**			**St. Err.**			**p-value**		
Licensee: Firm Size	**-0.257**	-0.037	-0.209	**0.103**	0.175	0.196	**0.013****	0.833	0.285
Licensor: Firm Size	-0.048	0.001	-0.105	0.080	0.041	0.209	0.550	0.989	0.617
R&D Intensity	0.919	1.885	0.640	1.734	1.397	2.792	0.596	0.178	0.819
Liquidity	-0.559	0.583	-0.845	2.614	1.957	2.990	0.831	0.766	0.778
Preclinical	-0.710	0.215	-2.120	0.711	0.316	1.851	0.318	0.495	0.253
Phase III	0.103	**0.973**	-0.744	0.886	**0.490**	2.105	0.907	**0.048****	0.724
Immuno-Oncology	**2.841**	1.336	3.142	**1.542**	0.889	4.085	**0.066***	0.134	0.442
Interaction: I-Oncology	**-0.422**	-0.114	-0.583	**0.191**	0.120	0.365	**0.027****	0.344	0.112
Cancer	**-2.810**	-0.833	**-4.394**	**1.163**	0.804	**2.640**	**0.016****	0.300	**0.097***
Interaction: Cancer	**0.432**	0.121	**0.628**	**0.170**	0.114	**0.297**	**0.011****	0.286	**0.035****
Constant	**3.880**	-0.660	5.283	**1.956**	2.822	3.254	**0.048****	0.815	0.105
Mean dependent var.	0.957	-0.152	2.446	SD dependent var.			9.942	3.967	14.383
R-squared	0.028	0.021	0.018	Number of obs.			984	564	420

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

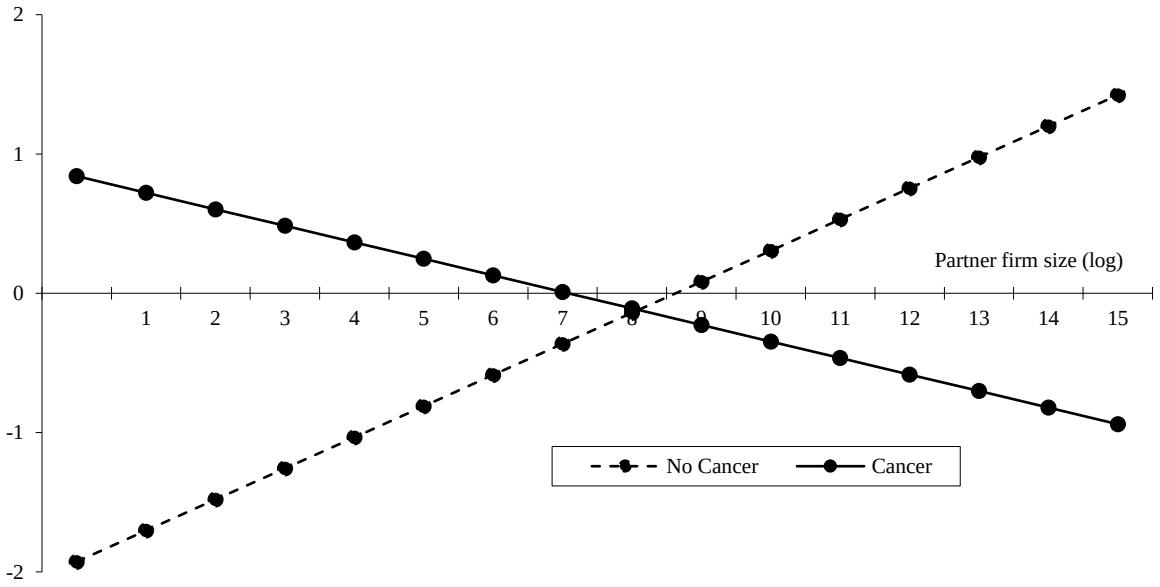
Regarding therapeutic area (**Hypothesis 5b**), we find no support for value appropriation or validation signals whenever an oncology drug is licensed, nor that immuno-oncology reflects an additional scarcity premium. This is the case for both sides of the agreement. Generally, it seems to be the case that therapeutic areas hold inferior explanatory power for licensing returns in a simple, binary form. In unreported regressions, we do not find that licensor or licensee returns are explained by any binary therapeutic variable and that controlling for development phase through interaction terms does not render meaningful results. Like Nicholson et al. (2005), we find that most therapeutic areas are insignificant determinants of the total value of

the deal, except for immuno-oncology. This raises the question why we do not observe a positive effect here, given that the changes in total deal value generally have a positive impact on returns.

Naturally, the lack of results could simply imply that the relationship between therapeutic areas and value creation is more complex than hypothesized in this study. It is plausible to assume that the differentiation between attractive and unattractive drugs is determined by the quality of the data generated during development and not necessarily by its categorized characteristics. Therefore, our variables may be unable to capture any validation or scarcity effects based on the quality of the underlying drug. Although the *Lemon-Hypothesis* may have been overemphasized in literature (Arora and Gambardella, 2010), the issue of genuine innovation in the pharmaceutical industry remains highly relevant, considering that the industry has been criticized for developing new drugs with few clinical advantages (Light and Lexchin, 2012).

Nevertheless, we find that interacting oncology and immuno-oncology with partner firm size provides very empirically meaningful results (see Tables 30 and 31). These results suggest that the value generated from oncology and immuno-oncology deals significantly depends on the size of the licensing partner, given statistically significant main effects and interaction terms. For the licensor, the market seems to view immuno-oncology deals between a large licensor and a large licensee as preferable to deals made with a small licensee. Interestingly, the relationship is exactly the opposite for oncology drugs, where a larger in-licensing partner is perceived negatively by the market (see Figure 16).

Figure 16: Marginal Effects of Cancer and Partner Firm Size on Licensor Returns



Given large standard errors and low average returns for large licensors, it is difficult to draw generalized conclusions from this. However, interaction terms also appear to be robust for licensee returns, where predicted returns are associated with much more narrow confidence intervals. Also, here, the market responds to therapeutic areas differently depending on the size of the licensing partner. Predicted returns for oncology as well as immuno-oncology deals both fluctuate above and below zero depending on the size of the licensor (see Figure 17). These results contradict the hypothesis that immuno-oncology constitutes scarcity and thus enables the licensor to appropriate value. However, they support the notion that small licensors could appropriate value in oncology deals. Obviously, the granular level of the empirical evidence in combination with weak theoretical backing pose difficulties for generalizations.

Figure 17: Marginal Effects of Oncology Areas and Partner Firm Size on Licensee Returns

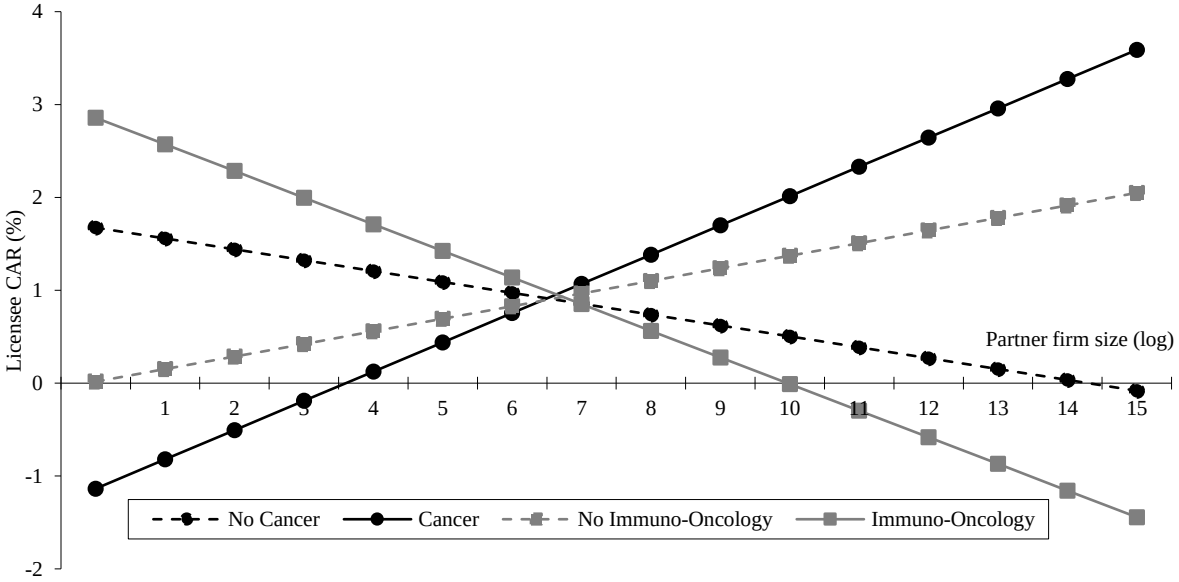
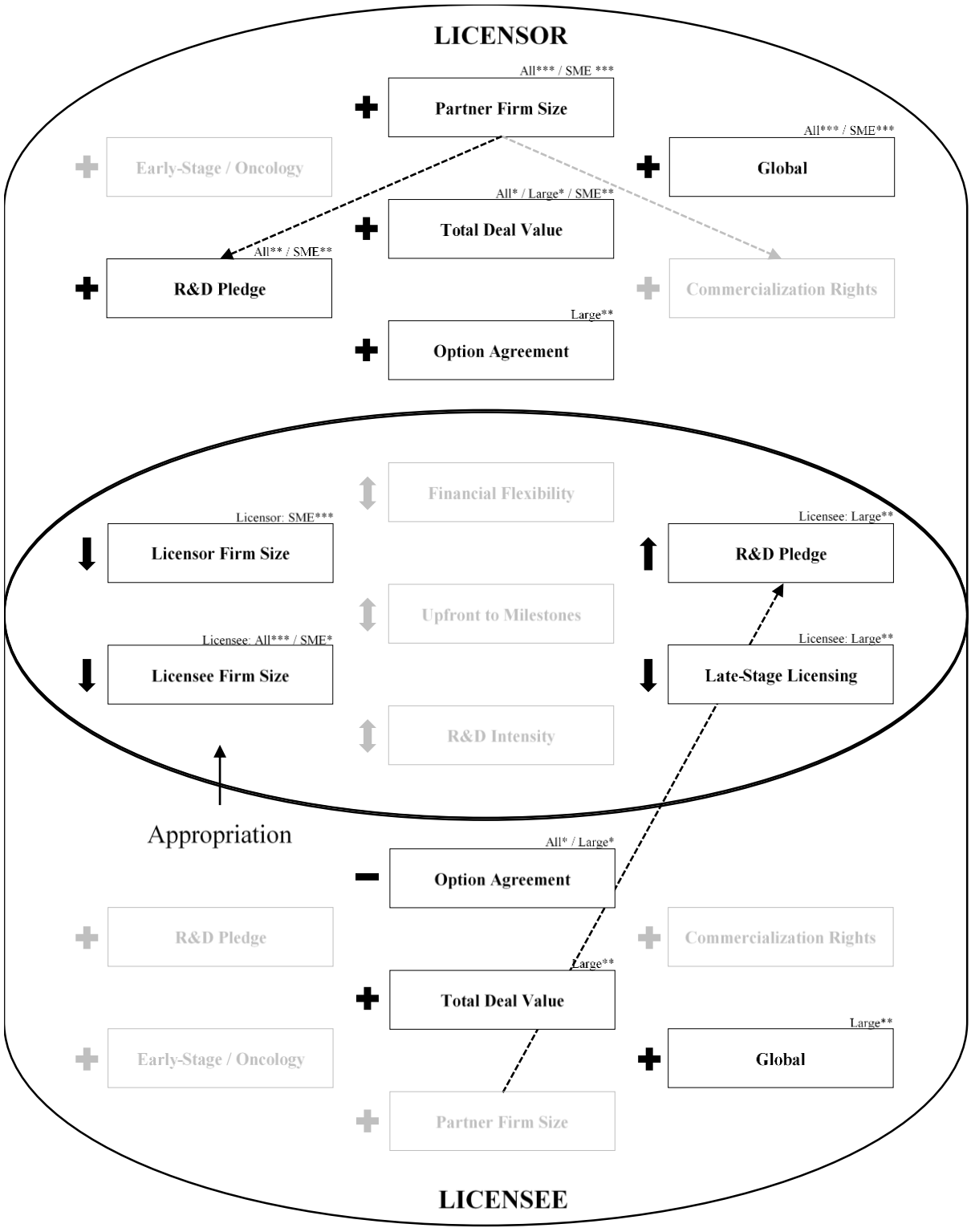


Figure 18 shows a summary of our findings using the same method of illustration as Figure 11 does. Greyed-out mechanisms are statistically insignificant. Mechanisms for which we found empirical evidence are shown with their respective significance written on top. Additionally, it is worth noting that licensor results appear to be more robust across sub-samples. Any findings unrelated to our hypotheses are not included in Figure 18.

Figure 18: Determinants of Value Creation and Appropriation



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

8. CONCLUSION

We contribute to the research frontier by painting a contemporary picture of the global licensing market and conciliating mayor strands of research regarding alliances and licensing in the pharmaceutical industry. We expand on existing considerations by introducing new variables specific to the pharmaceutical sector, while verifying the significance of existing ones. We propose that large firms can serve as intermediaries with a validating, and value-creating effect. We are able to produce statically and economically meaningful results, which add to the academic research frontier but might also be of relevance for industry practitioners. Like preceding research, we conclude that licensing deals generate value for both parties involved. However, the distribution of this value suggests that licensing deals are generally more favorable for the licensor. Results suggest that a major validation effect occurs on both sides of the licensing deal when the alliance partner is large. Similarly, we find that most deal characteristics extracted from the source data set are economically if not also statistically significant determinants of value creation and appropriation. These include payment characteristics, R&D pledges, option agreements and global commercialization rights. This suggests that the inclusion of licensing- and industry-related variables has added empirical value to our study, compared to a study with only firm-specific variables. The exclusion of information on the royalty agreement however is suboptimal and could prove to be an avenue of further research. Although we make an empirical contribution by investigating upfront and milestone payments, the theoretical framework considers a trifecta of payments. Moreover, the inclusion of royalty rates as well as the structure of the milestone payments would allow for a more granular empirical analysis. As of now, there is no way of telling whether a deal is front-loaded or back-loaded. Future research could investigate whether there are trade-offs between these payment types, how the market reacts to different distributions of deal value between them and whether the preferences are non-linear, as our results suggest. This likely requires

more quantitative data on royalty rates, considering that transforming text into binary variables does not appear to generate any meaningful results due to an extreme heterogeneity in values. This data issue is complicated by the fact that we note many tiered royalty rates as well as broad intervals for the royalty rate, which makes it difficult to pinpoint the effective royalty rate. Naturally, this may require a different empirical framework, as event studies with short-term returns may be ineffective in addressing initially undisclosed deal terms.

Albeit there are ways to extend on this study, as many explanatory variables could serve as dependent variables for other related research questions. Throughout the creation of this study, several interesting industry concepts have been revealed, such as the notion of a win/win proposition in licensing, the value share principle and alliance management. Although industry practitioners possess knowledge related to these areas, identifying literature that address these concepts is surprisingly difficult. Especially alliance management is a highly contemporary topic, considering that it is relatively new within the industry. As our study is focused on ex ante determinants of value creation and value appropriation, it would be of interest to observe the relationship between alliance management topics and long-term value creation in licensing. For example: How parties that have already entered an alliance deal with challenges related to conflicts of interest and moral hazards that emerge.

This study attempts to shed light on licensing practices in the pharmaceutical industry, which lead to its broad scope. Nevertheless, we have not been able to address many topics that go beyond the scope of our paper. We generally see large potential to generate knowledge when it comes to explicit theories of validation in licensing.

On a different note, despite the advantages of abnormal return event study methodologies, it seems paradoxical to rely on perceived value creation by the market to determine value creation given that R&D-intensive firms are associated with pronounced information asymmetries towards their investors. It would be interesting to see how the stocks of firms in licensing

alliances perform over longer periods of time. Long-run return methodologies however suffer from, in this case an obvious, endogeneity problem, which is avoided in short-term studies. Alternative return proxies, or a methodology that is more effective in dealing with endogeneity, could be able to investigate such long-term value effects. Nonetheless, the question remains if a market-based definition of value is what industry practitioners are concerned with. Albeit positive announcement returns suggest an increase in performance, they do not necessarily suggest an increase in innovation. How to maximize innovation output from alliances is a critical question for SME firms that the industry relies on to generate promising innovation.

The weak relationship between value creation and drug characteristics is disappointing, given that drug characteristics are given in a detailed form in dataset used for this study. Further analysis of the role of drug characteristics in value creation and appropriation is warranted, as well as the role of due diligence. One avenue is to explore drug trial data in combination with licensing agreements, and how the quality of the trial data influences the bargaining position of the licensor as well as the timing of entering a licensing agreement. This could potentially generate a lot of value for industry practitioners that seek to maximize the value of R&D.

Lastly, we acknowledge that our sample data is confined to a narrow range of years. This is not entirely negative; it may have amplified value appropriation tendencies, considering favorable market conditions. Nevertheless, for future researchers, it could be interesting to see if determinants of value creation and appropriation change as well as whether these results are robust when using samples from other or longer time periods.

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