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EXPERIENCE AND SIGNALING VALUE IN TECHNOLOGY LICENSING CONTRACT PAYMENT STRUCTURES

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When commercializing technology, the lack of proven results and a reluctance to invest upfront in resources hamper efforts by firms to work jointly with inventors to bring new discoveries to market. An effective contract payment structure—a mix of upfront and royalty payments—can help overcome these hurdles. We conduct our research in university technology licensing, where licensing managers act as intermediaries to unite inventors and licensee firms. Rather than leveraging their experience to bargain for maximum payments, highly experienced managers offer contractual payment structures that trade lower upfront payments for higher royalty payments in order to signal value. The signal instills confidence in the value of the partnership for skeptical licensee firms, and experienced licensing managers can amplify signals as needed to overcome the uncertainties inherent in technology commercialization. By explicitly addressing these variations in signal strength, we develop new theory that builds on classical signaling principles. We test and confirm these predictions in a sample of over 950 invention-licensing contracts. In addition to advancing signaling theory, our work has implications for academic entrepreneurship, and for how experience shapes value-sharing agreements in collaborative innovations.

"Be careful not to compromise what you want most for what you want now"

Zig Ziglar

In the market for innovative technologies, the successful commercialization of new discoveries often depends on bringing multiple parties together. Inventors may push the frontiers of science, but often lack the skills and resources needed to bring their breakthroughs to market. And while firms desire cutting-edge products to stay competitive, they prefer not to take on the risky efforts of basic scientific research that require significant investment, but yield few discoveries (Teece, 1986). Given these complementary interests, opportunities to collaborate should appeal to both sides. However, potentially fruitful collaborations are often stymied by a buyer's reluctance to commit to still-unproven products and technologies (Dushnitsky, 2010). With limited verifiable information regarding the market potential of a nascent innovation, buyers (licensees) wish to invest as little as possible, especially upfront, whereas sellers (inventors) seek as much as possible upfront to minimize the risks associated with developing their technologies (Gans & Stern, 2003). To break through this impasse, buyers and sellers of technology depend on intermediaries to craft an effective *contract payment structure*—a mix of upfront and performance payments—as compensation for the risks associated with commercializing a new technology, and motivation for the rewards that follow a successful effort (Shane, 2001). Designing a contract payment structure that satisfies all parties is extremely difficult in practice, so intermediaries rely on experience to construct the best agreements.

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Experienced intermediaries can construct the payment structure in one of two ways. A conventional bargaining approach suggests that experience will lead intermediaries to use their skills to their own advantage (seeking higher upfront payments *and* royalty payments). In this approach, experienced intermediaries will use the contract payment structure to resolve clashing interests with a "winner-take-all" objective of seeking greater yields for the inventors. Alternatively, experienced intermediaries, who are more certain about the value they create, could also propose a tradeoff involving a lower upfront *but* higher royalty payment. Experienced intermediaries are able to offer this latter contract payment approach because of their ability to select more promising opportunities and match them to capable partners. When designed by skilled intermediaries, contracts that signal value and minimize risk can effectively create more shared value.

Signaling the value of an unproven innovation is a key element in promoting collaborations between skeptical parties; as such, we use signaling theory to understand how contract payment structures operate in technology licensing. When employed effectively, signals can address the obstacles that prevent agreement between parties when quality cannot be directly observed (Stiglitz, 2000). There is a long tradition of studying how and why signals operate in wide-ranging contexts from labor markets (Spence, 1974) to financial performance (John & Williams, 1985) to evaluating investment opportunities (Plummer, Allison, & Connelly, 2015). Within this body of research, our comprehensive review revealed two areas in signaling theory that require further investigation. First, theoretical models predict a better-informed party signals potential value by changing the contract structure to prioritize future risky payments over fixed upfront payments (Beggs, 1992; Gallini & Wright, 1990; Macho-Stadler, Pérez-Castrillo, & Veugelers, 2008). Although theoretical models assume that the sender possesses superior information, in practice senders do not always possess this *ability* to hold superior information (Hegde, 2014); we lack studies investigating the source of information. Second, signals are beneficial when information on quality cannot be easily verified. However, research on signals has not always investigated this *need* to signal when receivers are poorly informed about a technology's true value (Ozmel, Reuer, & Gulati, 2013; Ramchander, Schwebach, & Staking, 2012). This could be the reason why signaling research about payment structures contains mixed findings (Hegde, 2014; Lafontaine, 1993; Macho-Stadler et al., 2008; Shane, Shankar, & Aravindakshan, 2006). By considering intermediary experience, we can address these two shortcomings in signaling theory—integrating signaling ability and need into a unified framework—to better understand how parties agree on contract payment structures. This is vital because signals are costly: signaling can be counterproductive for senders who signal inappropriately or when the need is not as great.

By knowing how to select promising inventions and match them effectively to capable licensees, experienced intermediaries can create and signal greater commercial value to skeptical buyers through contract payment structures that offer lower upfront payments and higher royalty rates. With experience, signalers learn how to alter the contract structure to convey potential and encourage hesitant parties to collaborate (Holcomb, Holmes, & Connelly, 2009; Lepak, Smith, & Taylor, 2007). Lower upfront payments reduce concern over uncertain results and demonstrate confidence about the opportunity's value. At the same time, higher royalty payments shift the risk toward the intermediary (since payments are delayed) and signal the potential value to the buyer (since payments depend on future performance). In this way, the added value benefits all parties and does not simply reward intermediaries (and the sellers they represent) unilaterally for their own advantage.

We conducted our study within the context of a technology transfer office (TTO) at a large public U.S. university. In this setting, the TTO's licensing managers seek opportunities to license and commercialize technology produced at the university through outside firms. We analyze how experienced licensing managers employ their signaling ability (from better knowledge of an invention's value) amid varying levels of signaling need (resulting from technological uncertainty)—two conditions not explicitly accounted for in prior research. Based on our analysis of over 950 invention-licensing contract pairs, we present evidence for how experience (ability) influences contract payment structure combinations (upfront fixed-fees and royalty rates) and for how three contingencies (need to signal)—science-intensive inventions, inventor experience, and patent scope—affect this main relationship.

Our study offers several contributions. By making use of signaling theory, our work demonstrates how intermediaries signal value credibly and effectively through contract payment structures (the tradeoff between upfront and royalty payments). We pinpoint how experience influences contract choices resulting from selecting promising technologies and matching them with capable commercialization partners (expanding on baseline ideas from Connelly, Certo, Ireland, & Reutzel, 2011; Ndofor & Levitas, 2004). By examining contingencies to the relationship between intermediary experience and contract payment structures, we illustrate how signals can be adjusted depending on the sender's ability or the need for a stronger signal. These insights have practical implications for commercializing new ideas (building on principles articulated by Grégoire & Shepherd, 2012; Shane, 2000) and aligning incentives to motivate each party to expend the necessary effort to bring opportunities to fruition (complementing the foundational concepts from Bazerman & Neale, 1985 and March & Olsen, 1989).

TECHNOLOGY TRANSFER AND CONTRACT PAYMENT STRUCTURES

The technology-licensing context is an appropriate setting to study how contract payment structures are crafted. The commercialization of academic science is a high-risk activity, so determining the payment structures for licensing technology can be complex. Often, significant upfront investments are needed just to bring initial discoveries to a proof-of-concept stage, and much more additional funding to actually bring a product to market. Given the high costs and probability of failure, the buyers (licensees) wish to minimize their upfront investment, whereas inventors seek upfront payments to maximize their own return. Almost all university licensing agreements contain some combination of an upfront fixed-fee payment and a royalty rate to balance these concerns (Jensen & Thursby, 2001). These two components form the core of the contract payment structure.

Technology Transfer Office Study Context

We examined the determinants of the contract payment structure by studying a TTO that is one of the oldest and largest of its kind in the U.S., with an endowment of over $2 billion. As the licensing arm of a large U.S. university, the TTO generates over $50 million annually from its portfolio of inventions. We visited the TTO regularly to conduct interviews with its senior management, intellectual property managers, licensing managers, and legal counsel to develop a deeper understanding of the TTO's licensing processes. These interviews allowed us to understand how decisions were made regarding the contract payment structures of the TTO's licensing agreements.

Our setting involves three parties: the inventor (seller), the licensee firm (buyer), and the TTO licensing manager (intermediary). The TTO and its licensing managers serve as intermediaries[1] between inventors—who tout the possibilities, usefulness, and potential of their discoveries—and the licensee firms—who are more skeptical in their assessment of a new technology's profitability (Wennberg, Wiklund, & Wright, 2011; Wright, Clarysse, Lockett, & Knockaert, 2008). The inventor's and the TTO's (represented by the licensing managers) incentives are closely aligned, as they share the licensing income in a fixed proportion. As such, both will seek to earn a higher licensing income. The licensee, on the other hand, seeks to pay as little to the inventor and the TTO, and as far along in the technology development process, as possible.

Among the different positions in the TTO, our study focuses specifically on the licensing manager role, since they play an important part in designing the contract payment structure for licensing agreements. Licensing managers help secure the TTO's annual revenue, which comes from the successful commercialization of innovations conceived in the university setting. As a matter of university policy, all employees are obligated to disclose their inventions to the TTO, even if they want to commercialize their inventions themselves. At monthly meetings, these inventions are discussed for their licensing potential and their likelihood of receiving patent protection. If the inventions are favorable on both dimensions, the TTO will file for a patent and pay for attorney and initial filing fees. The invention is then assigned to a licensing manager, who works with the inventors to find a suitable firm to license the technology.

Contract Payment Structure: Upfront Fixed-Fee Payments and Royalty Rate

One of the defining features of technology licensing is the way in which the contract payment structure is designed between the buyers and sellers. Not

[1] In our study, intermediaries may choose to send signals through their contract designs and licensing managers serve as the principal intermediaries. For ease of exposition, we use "intermediary" and "signal sender" when making general arguments and "licensing manager" when making specific arguments related to our context.

only do both parties have opposite preferences for the total size of the payment, but they also have conflicting preferences for how that payment should be structured. The buyers of inventions (licensees) would prefer to pay as little upfront as possible to minimize their risk and the uncertain outcomes they face. Their goal is to delay payments and make them contingent upon the invention's performance through a *royalty rate* (Gallini & Wright, 1990; Macho-Stadler et al., 2008). Conversely, economic theory predicts that for multiple reasons—such as risk aversion and financial constraints—the suppliers of inventions (the inventors in our context) will prefer high *upfront fixed-fee payments* for an invention (Crama, De Reyck, & Degraeve, 2008; Kulatilaka & Lin, 2006). Licensing managers negotiate fixed fees for the reimbursement of patent filing fees and other upfront costs required for commercialization. These are substantial investments—initial filing fees can range from $30,000 to several hundred thousand dollars for a broad, defensible patent claim in the U.S. and international markets. As such, any decision to trade off certain short-term payments for uncertain royalties is a costly one.

Experience and Contract Payment Structure Design

At this point, it is helpful to consider how experience influences the design of the contract payment structure in technology licensing. We begin with the basic assumption that, with experience, licensing managers have a better ability to craft agreements that bring buyers and sellers together to commercialize the technology. One pathway to agreement is through bargaining and using the power that comes from greater knowledge to claim a larger share of the value created. We know from research that bargaining power gets stronger with experience (Neale & Bazerman, 1985). As experienced licensing managers learn about opportunities through their industry contacts and professional networks, they are better positioned to leverage this knowledge to bargain for more favorable contract terms. This perspective assumes that through effective bargaining, the clashing interests between buyers and sellers are settled in the contract payment structure. Since the focus of this strategy is about gaining an advantage, this approach will likely lead to one party (the TTO) benefitting at the expense of the other (the licensee) if the contract is accepted with simultaneously higher upfront fees and royalty rates.

Experienced licensing managers can follow another pathway to design a contract payment structure that unites all parties toward a common outcome. This alternative strategy requires licensing managers to determine whether commercial value can be created, as a result of selecting a specific invention to be licensed to a particular firm. Experience allows licensing managers to make this determination (through selection and matching) with greater certainty. To entice firms to enter into a licensing agreement, experienced licensing managers design a contract payment structure that lowers the upfront fixed-fee payment in favor of a performance-based royalty. They use this as a signal to convey potential quality to prospective licensees. In the following section, we describe the conceptual framework for how signals operate and why they can be an effective means for addressing information asymmetry between buyers and sellers of technology.

INFORMATION ASYMMETRY AND SIGNALING

Information asymmetry is a fundamental and persistent concern affecting the commercialization of new inventions (Gallini & Wright, 1990; Macho-Stadler et al., 2008). On the supply side, highly scientific discoveries are difficult to evaluate because their quality and success depend on multiple dimensions, which may not be fully apparent in nascent products or services. On the demand side, there are uncertainties as to whether partners can successfully bring an innovation to market. Success depends on the partners' ability to absorb the academic science, the extent of their market reach, and the breadth and depth of their product portfolio (Arora & Gambardella, 1994). Therefore, standard economic theory predicts that without any intervention, the information asymmetry between the risk-averse inventor and licensee will prevent mutually beneficial collaborations. Scholars have studied different mechanisms to overcome this friction. One such intervention is the use of signals.

When properly deployed, a signal serves to bridge the gap caused by information asymmetry between the multiple parties who seek to enter into a collaborative agreement (Audretsch, Bönte, & Mahagaonkar, 2012; Spence, 1973). Signals and signaling have the following characteristics: (1) Signaling occurs when the better-informed party (sender) moves first and provides an indication of the underlying quality to the uninformed party (receiver); (2) The signal is *credible* if the investment that is made by the sender is costly and irreversible; (3) The signal is *informative* if the magnitude of the cost to signal is dependent on the underlying quality of the sender (Spence, 1973: 358). The uninformed party (the recipient) receives the signal and enters into a contract that fits their assessment of the sender's underlying quality. Although all credible and informative signals are costly, some senders are able to produce signals at a lower relative costs than others. According to signaling theory, senders representing a higher quality have a lower cost of investing in a signal than those who have a lower quality.[2] Therefore, senders representing higher quality are more likely to make the investment to emit a signal. Conversely, for senders representing lower quality, the cost of investing in a signal is higher than its return, making a signal an unattractive investment.

We argue that our setting is ideal for confirming and informing the predictions of signaling theory, because it combines four desirable aspects of signals and their senders: a signal sender with varying *ability*, situations with different *need* to signal, in which the signal, changes in price, are sent with *intentional purpose* to *specific* receivers. We refer to Appendix A for a summary of applications of signaling theory.[3] This survey also reveals that despite pricing being much studied in theoretical economic models as a signaling tool, it has received relatively little attention in the management literature. In the studies that combine these characteristics of signals and senders, the findings are mixed (e.g., Etzion & Pe'er, 2014; Kirmani & Rao, 2000).

Signal Sender Characteristics

Much of the literature assumes that senders have a constant ability to signal, and that the baseline need to signal does not vary. For example, the earliest signaling literature studying the role of education in the labor market (Spence, 1973) assumes that education is undertaken once and that the ability of the signal sender—the potential employee—is invariant. This reduces the adaptability of the signal to suit the evolving abilities or needs of the signal sender, which erodes the value of the signal over time (Merluzzi & Phillips, 2016; Sauer, Thomas-Hunt, & Morris, 2010). Our setting, in which the licensing manager's experience varies with time, allows us to explore whether and how experience of the licensing manager or the inventor affects signaling ability and the signals being sent.

The literature on signaling is unanimous in finding that the need for signaling is greater in more uncertain environments (Hsu & Ziedonis, 2013; Ozmel et al., 2013; Ramchander et al., 2012). However, not all signals can be strengthened in the face of greater uncertainty. For instance, some signals are impossible to alter unilaterally, such as reputation, which is both path-dependent (Lee, 2010; Pollock, Lee, Jin, & Lashley, 2015) and relative (Huang & Washington, 2015). This weakens the accuracy of the signal in the presence of greater information asymmetry. In our context, we would expect that inventions at different stages of development, produced by different levels of inventor experience, or with a wider range of applications may influence the licensee's need for information about the invention. These conditions create uncertainty for the licensee about the invention's potential commercial value.

We refer to the concept of signal strength (also called signal fit), which is a central attribute of a signal: it is "the extent to which the signal is correlated with unobservable quality" (Connelly et al., 2011: 53). To the extent that senders learn from experience and improve their quality over time, we argue that they will adapt their signal strength to their ability and need to communicate with uninformed receivers. Increasing signal strength may be necessary under certain conditions when an even stronger signal is needed to overcome baseline doubts caused by high information asymmetry.

Signal Characteristics

To ensure that an action is an unbiased and clear signal, it is important to know whether it is sent with an intentional purpose and for a specific receiver. For example, the signaling value of a company's network is influenced by the fact that the company originally pursued partnerships for a variety of

[2] An often-cited example is the value of higher education in the employment market. Employers—the uninformed party—may find it hard to evaluate the quality of potential workers. The workers, however, know their own ability and can choose to invest time, effort, and resources in pursuing higher education. Workers with higher ability can achieve the same level of higher education but with a lower investment of time, effort and resources than those with a lower ability. The employer uses the education level as a signal and offers wages that differ depending on the higher education level of the worker. The equilibrium separates if workers with lower ability opt not to undertake higher education because the higher wages do not sufficiently compensate for their higher cost of achieving that educational level.

[3] To conserve space, we provide a much more comprehensive literature review of the signaling literature (based on over 110 articles) involving these four characteristics in Appendix A.

reasons *not* linked to signaling (Reagans, Singh, & Krishnan, 2015; Reuer, Tong, & Wu, 2012; Stuart, 2000). Similarly, studies on corporate announcements report that these signals are broadcast to multiple parties, rather than crafted to suit a unique counterparty, limiting the sender's ability to tailor the signal to the recipient (Gomulya & Boeker, 2014; Stern & James, 2015). However, in our setting in which each contract is a unique negotiation outcome between the TTO and the licensee firm, variations in the contract terms can be made freely to reach a collaboration agreement tailored for the relationship. In the TTO context, the contract structure variation is an intentional signal sent to specific receivers. Since misguided or misdirected signals can have costly consequences, we investigate how varying ability and need affects signaling effectiveness. Information asymmetry and risk aversion among potential partners create the *need* for a complex payment structure, but it requires the licensing managers' *ability* to skillfully design contractual agreements in ways that signal enough value to actually bring parties together.

In the following sections, we present a set of study predictions and their supporting rationale. We offer details about the mechanisms behind why licensing manager experience leads to variations in upfront fixed-fee payments and royalty rates. We also investigate sources of greater information asymmetry (science-intensive inventions, inventor experience, and wide patent scope) that represent contingencies to this main relationship and situations for adjusting signal strength. Given the lack of published research on these mechanisms, we formulate our arguments by deriving our own theoretical model and supplementing with insights from the broader signaling literature.

STUDY HYPOTHESES

Value of Licensing Manager Experience

Before articulating our arguments for how experienced licensing managers signal value through their contract payment structure, we first establish whether experience actually matters for higher licensing revenues from new technologies. This would justify further investigation into how and why experience matters for the contract payment structure itself. Consistent with research on managerial ability and experience, we assume that skilled licensing managers accrue knowledge from past efforts creating value in similar contexts (Holcomb et al., 2009; Lepak et al., 2007). We examine if such knowledge actually translates into commercial success of the inventions they license.

One baseline argument for licensing experience is that it improves one's bargaining ability to negotiate for higher licensing income. From a bargaining perspective, we expect that licensing managers with experience can gain insight into how to persuade parties to agree on performance-based contract parameters (Ruckman & McCarthy, 2017). The baseline expectation is that experienced licensing managers use the contract payment structure to bargain for as much as possible from their licensees while minimizing their own risk. This appears reasonable because experience provides licensing managers with a greater store of scenarios to draw from, which can be used to negotiate more confidently.

Besides the bargaining argument, there are other reasons for the experience–performance relationship. From research in entrepreneurship and other related contexts involving nascent technologies, we know that experience provides additional knowledge that could translate into better performance. For example, experienced entrepreneurs identify more valuable economic opportunities by having a higher threshold for performance (Chatterji, 2009). They forecast with better accuracy (Cassar, 2014), raise resources more quickly (Zhang, 2011), and heavily depend on their experience to guide them in familiar markets or technological domains (Eesley & Roberts, 2012). We tailor these insights into a specific rationale for the technology-licensing context. We argue that experienced licensing managers generate value through two mechanisms: improved selection of promising inventions, and better matching with capable partners.

First, experienced licensing managers *select* more promising new inventions for commercialization (Hoppe & Ozdenoren, 2005; Macho-Stadler et al., 2008). They are able to identify the best inventions based on their earlier licensing agreements and ongoing interactions with current licensees. With this knowledge, licensing managers can offer inventors suggestions to improve their technology's appeal to potential licensees (Alexander & Martin, 2013; Ruckman & McCarthy, 2017). This begins with initiating extensive pre-licensing dialogue with inventors. Through these conversations, licensing managers deepen their understanding of an invention's potential commercial applications, its most receptive markets, technological limitations, and what additional development may be required for successful commercialization. Experienced licensing managers may request more data from inventors or ask them to run additional experiments, knowing that this information will be critical for attracting licensees.

Second, experience prepares licensing managers to better *match* inventions with licensing firms and more effectively persuade them to strike a bargain (Faems, Janssens, Madhok, & Van Looy, 2008). Licensing managers are responsible for marketing inventions and searching for potential licensees. Having negotiated past agreements widens a licensing manager's network of potential licensees. Access to this larger pool reduces search costs and ultimately increases the odds of securing a good match (Hoang & Rothaermel, 2005; Mortensen, 1988). When past deals were constructed with performance-based contracts, the ongoing business development reports that licensee firms submit provide licensing managers with up-to-date industry information and market conditions that affect the latest technology's implementation. This deeper knowledge helps licensing managers discern which markets and firms are most likely to benefit from the invention, leading to inventor–licensee collaborations with higher value-creation potential (Gompers, Kovner, Lerner, & Scharfstein, 2006; Mindruta, 2013; Shane, 2000). For these reasons, we predict:

Hypothesis 1. Licensing manager experience is positively related to the commercial success (licensing revenue) of the licensed invention.

In the first prediction, we simply reasoned that experience matters for commercial success without specifying a particular pathway for this relationship. We now contrast two pathways—better bargaining skills, versus value creation through selection and matching—by focusing on the two elements of the contract payment structure itself. The impact of better bargaining skills on the contract structure is obvious: as the licensing manager gains experience, they also gain a greater ability to negotiate for larger upfront *and* royalty payments. By contrast, we predict from signaling theory a different outcome from experience: that greater commercial success results from trading lower upfront fixed-fees in return for higher royalty rates. Moreover, the magnitude of this tradeoff depends on the extent to which information asymmetry clouds the assessment of an invention's commercial potential. In the following sections, we provide our rationale for this alternative course. We draw on the signaling literature to establish general principles and then present arguments based on our theoretical model for the mechanisms addressed in our study.

Experience and Signaling Through Contractual Payments

Under conventional bargaining principles, we would expect risk-averse licensing managers to seek to capture as large a share of commercial revenues as possible and avoid scenarios that could jeopardize guaranteed income, especially in the short-run. This means that licensing managers would attempt to increase their own fraction of the invention's total value without convincing the licensee of the greater total value. This would lead us to see the most experienced licensing managers offering contracts that are higher in upfront fixed-fee payments than those negotiated by inexperienced managers. This type of agreement minimizes the licensing managers' downside risk, while still offering the upside of future returns.

Formal theoretical work on signaling theory, however, offers a different pathway for creating agreements. We argue that licensing managers deploy signals of value-potential through contractual payment structures, by varying the two main components of a typical licensing contract—upfront fixed-fee payments and performance-based royalty rates (Gallini & Wright, 1990; Macho-Stadler et al., 2008). From signaling theory, we know that a privately informed signal-sender conveys higher quality by offering costly concessions—in our context, this means presenting contract terms with a lower upfront payment paired with higher royalty rates. By doing so, licensing managers display their willingness to bear the additional cost and risk of forgoing guaranteed income in return for uncertain longer-term gains (Sanders & Boivie, 2004). Such a contractual design is based on the licensing manager's confident assessment that the resulting change in total royalty revenue (the royalty rate multiplied by value) will ultimately compensate for the decreased upfront payment (Gallini & Wright, 1990; Martimort, Poudou, & Sand-Zantman, 2010). This type of agreement structure offers a credible signal to risk-averse licensees, who are unlikely to give credence to mere "cheap talk" or persuasion by the licensing managers.

To date, neither the formal theoretical work nor the empirical research published in the signaling literature integrates experience as the basis for accruing superior knowledge. Thus, we develop our own theoretical model to address this shortcoming

(Appendix B provides full details). We argue that the licensing managers' level of experience determines their overall expected revenue from royalties. While the decreased upfront payment is valued identically, regardless of experience level, an increased royalty rate creates higher expected revenue for the experienced licensing manager. Highly experienced licensing managers can exploit this difference to credibly signal their expertise, and, by extension, the value they create. Experience improves the cost-benefit tradeoffs between the lower (but certain) fixed-fee and higher (but uncertain) royalties.

If highly experienced licensing managers are willing to give up some upfront payment, they can offer a contract with a costly and credible signal and obtain more value. The signal is costly because they must forgo a guaranteed upfront payment, and credible because the royalty rate is set such that a less experienced licensing manager would not be sufficiently compensated for the decrease in upfront payment. As the experienced licensing manager creates more value, however, the royalty rate increase not only compensates for the upfront payment, but also generates additional revenue. Therefore, the highly experienced licensing manager prefers to offer a signaling contract.

Thus, under the signaling framework, the experienced licensing manager signals a greater invention value through a higher royalty rate and lower upfront payment, yielding higher total licensing revenue, but limiting how much revenue can be obtained from the licensee upfront. Rather than using their skills to *bargain* for a larger share of the created value, highly experienced licensing managers prefer to *signal* their proficiency in selection and matching to create high-value collaborations. For these reasons, we predict:

Hypothesis 2. As licensing manager experience increases, the upfront fixed-fee payment decreases while the performance-based royalty rate increases.

Contingencies in the Experience–Signal–Strength Relationship

Having established the primary relationship between experience and payment-structure outcomes, we turn our theory development to three invention-related contingencies that affect this primary relationship: science-intensive inventions, inventions produced by experienced inventors, and inventions with broader patent scopes. Each of these characteristics varies the amount of information asymmetry that all parties must address when evaluating potential agreements. As information asymmetry and valuation uncertainty vary, so too will the *need* to transmit a signal regarding quality and value-creation potential. As in our main predictions, the modulation of signal strength will be reflected in tradeoffs between fixed and royalty payments.

Licensing managers use their experience to determine signal strength that appropriately corresponds to the need. When information asymmetry increases, experienced licensing managers will transmit a stronger signal by taking even less upfront and shifting more of the payment to royalties, to show their confidence in the invention's value and willingness to absorb more risk. By contrast, in the absence of experience or when information asymmetry is lower, the ability or need for a strong signal is not as high, and licensing managers will not shift as extensively to royalty payments or sacrifice guaranteed upfront income.

We break new theoretical ground by examining the interaction between experience (ability) and changes in information asymmetry (need for signaling) that results in adjusting signal strength (reductions in upfront fixed-fee payments and increases in royalty rate). Recall that experience provides licensing managers with better insights into *selecting* promising inventions to license and *matching* them with capable licensees. Depending on the particular need for signaling, licensing managers will draw more heavily on their experience to use either one or both of these skills. In the following sections, we detail the rationale for each contingency and their corresponding predictions.[4]

Adjusting Signal Strength: Science-Intensive Inventions

When inventions are science-intensive, information asymmetry regarding their value makes signals harder to interpret (Heeley, Matusik, & Jain, 2007), and uncertain financial returns make them difficult to license (Hagiu & Yoffie, 2013). Therefore, sending an even stronger signal becomes more important when appealing to reluctant licensees amid higher information asymmetry (Coff & Lee, 2003; Ozmel et al., 2013; Ramchander et al., 2012). Accordingly,

[4] For our moderating hypotheses, we expand the theoretical model introduced in Hypothesis 2 and use these features to develop our rationale for Hypothesis 3–Hypothesis 5. To conserve space, we omitted the graphs and detailed numerical examples in the main text and Appendix B.

some scholars have predicted a stronger reliance on royalty payments as a strategy for licensing science-intensive inventions (Balmaceda, 2009; Fuller & Blau, 2010). Our focus takes this one step further by examining the interaction between change in the licensing environment (greater uncertainty due to increased science intensity) and change in ability of the signal sender (greater value creation through an experienced licensing manager) and their combined impact on payment structures.

When selecting high-value opportunities, licensing managers consider how far along inventions are in their development. Mature inventions contain a higher degree of applied science and have verified results regarding their profitability. This makes it easier for licensing managers to envision more valuable opportunities based on well-defined information. With little uncertainty, experience does not play as much of a role in determining the contract structure, because the need for signaling is less important (Ozmel et al., 2013; Ramchander et al., 2012).

When licensing less-developed inventions, however, experience through selection and matching becomes more relevant. Without deep connections to existing technologies, these inventions are much more "science-intensive" and linked to academic research rather than commercial applications. With commercial prospects less defined, licensing managers must use their experience to envision valuable opportunities that will not be initially apparent to prospective licensees. As a result, the potential value of these inventions will vary, making it more difficult to match to the best-suited licensee (Amram, 2005). Larger variability increases the risk of royalty payments, making less experienced licensing managers reluctant to reduce upfront payments (Sanders & Boivie, 2004). However, experienced licensing managers—who are more knowledgeable about the underlying science—can more reliably select high-value inventions, even if an invention is based on less developed, more academic science (Shepherd & DeTienne, 2005). In this case, finding the appropriate partner who can commercialize an early-stage invention is both more difficult and more crucial. Experienced licensing managers perform better matching by knowing current industry trends and keeping tabs on which firms are best equipped to absorb and integrate new science into commercial applications (Baron, 2006). This lowers the overall risk of constructing collaborations that involve early-stage inventions, making upfront payments less necessary than they would be for less experienced licensing managers. Taken together, the value that a more experienced licensing manager can provide is amplified in highly scientific inventions, and therefore the signal strength will be correspondingly amplified as well.

> *Hypothesis 3. For inventions heavily dependent on academic science, the upfront fixed-fee payment decrease (Hypothesis 3a) and the royalty rate increase (Hypothesis 3b) become more pronounced as licensing manager experience increases.*

Adjusting Signal Strength: Experienced Inventors

Inventors experienced in licensing are knowledgeable about working with industry and their commercialization capabilities. Knowing the needs of potential industry partners, inventors can elect to work on problems that are of particular interest to them. Furthermore, past interactions give experienced inventors a better awareness of the challenges inherent in transferring academic science to a licensee (Zander & Kogut, 1995). Therefore, the process of technology transfer will be more straightforward for experienced inventors and will lead to producing academic science that is more valuable to the licensee (Shane, 2000).

Licensing manager experience also provides additional and complementary value to inventor experience. Because a licensing manager's experience is more market-related, their selection criteria will not fully overlap with the inventor's criteria and will be more selective with greater experience even when working with experienced inventors. Moreover, an experienced licensing manager can better communicate with the inventors, allowing for a fuller understanding of the inventor's own efforts at creating value (Tushman & Scanlan, 1981). This is especially useful since experienced inventors generate more inventions, but these discoveries come with higher variability in their probability of being a breakthrough (Conti, Gambardella, & Mariani, 2013). As the inventions taken forward for licensing have passed both the selection processes of the experienced inventor and licensing manager, they are more valuable and better aligned to external opportunities.

Because a licensee does not have a priori knowledge about an inventor's licensing experience, the licensing manager needs to signal the value that is created by the double selection from both the inventor and their own experience. Thus, an experienced licensing manager who represents an invention from an experienced inventor is confident in much larger value creation potential. This higher expected value increases the experienced licensing-manager/inventor team's ability to send a stronger signal: a larger reduction in upfront payment, with a larger increase in royalty rate.

The matching mechanism of licensing manager experience is likely to be muted for experienced inventors. Past research has found that licensing managers rely on inventors to help generate leads within their network (George, 2005; Jensen & Thursby, 2001). These leads are likely to be particularly useful when the licensing manager lacks experience. However, they do not add significant value to the experienced licensing manager, whose network is already quite large without the inventor's contribution. Therefore, the matching mechanism decreases in importance as licensing manager experience increases when dealing with inventions by experienced inventors.

When inventors are not as experienced, they lack knowledge in evaluating commercialization opportunities and may disclose inventions to the TTO that are not appealing to industry (Shane, 2004). Although licensing managers will be more selective as they learn to patent and license (George, 2005; Mowery, Sampat, & Ziedonis, 2002), the upside value is limited for inventions submitted by inexperienced inventors because their discoveries are inherently less valuable. As a result, experienced licensing managers are less willing to send a strong signal for inventions by inexperienced inventors. To summarize, as licensing managers represent inventions by experienced inventors, their ability to send a signal through the payment structure increases, because the value created from joint experience makes signaling less expensive. Experienced managers will thus employ stronger signals to reflect this greater value. For these reasons, we predict:

Hypothesis 4. For inventions by experienced inventors, the upfront fixed-fee payment decrease (Hypothesis 4a) and royalty rate increase (Hypothesis 4b) become more pronounced as licensing manager experience increases.

Adjusting Signal Strength: Patent Scope

An invention with a narrow patent scope is easier to match, regardless of the licensing manager's experience. When an invention has a wide *patent scope*, however, it has the potential to be applied in many different industries and create greater value (Lerner, 1994). To fully realize these additional opportunities, the licensing manager needs to match the invention to the best licensee not only within an industry, but also across industries. Therefore, licensing manager experience is a stronger driver of signaling when the patent scope is wide than when it is narrow; superior matching can create significant value for a wide patent scope, but this is only possible for licensing managers with experience, due to the difficulty of identifying the most promising licensee in the most attractive industry. While the importance of experience on *matching* is critical for wide-patent-scope inventions, the impact from the *selection* mechanism is less important: when inventions have a wider patent scope, they have more opportunities to be commercialized across many different industries, so value can still be created if a good match with a licensee is found (Lerner, 1994; Merges & Nelson, 1990).

To signal greater value resulting from a wider patent scope under information asymmetry, licensing managers need to send a stronger signal to prospective licensees. We know signal interpretation varies among audiences (Gomulya & Boeker, 2014; Reuer & Ragozzino, 2012): receivers react to signals differently depending on their own information (Soh, Mahmood, & Mitchell, 2004), and are more likely to heed the signal if they conclude that the signal or the signal sender will create value for them (Chatterjee, Harrison, & Bergh, 2003; Marquis & Qian, 2014). When evaluating inventions with a wider patent scope, licensees are more likely to be uncertain about whether they are a suitable match for the invention, and will be more receptive to the licensing manager's signal to overcome these doubts. We argue that experienced licensing managers understand this, and will shift the contract payment structure to offer contracts with more pronounced increases in royalty rates and decreases in upfront payments. For inventions with a narrow patent scope, information asymmetry due to matching concerns is lower and thus corresponds with a reduced need to signal, making them less dependent on licensing manger experience.

To summarize, as licensing managers seek prospective licensees for inventions with a wide patent scope, they need to send a stronger signal in their payment structure to overcome information asymmetry in the matching process. Experienced managers understand this need and employ their insights to design stronger signals. For these reasons, we predict:

Hypothesis 5. For innovations with a wide patent scope, the upfront fixed-fee payment decrease (Hypothesis 5a) and the royalty rate increase (Hypothesis 5b) become more pronounced as licensing manager experience increases.

DATA AND METHODS

As described earlier, we tested our predictions using original data from the TTO of a prominent U.S. university. Similar to the MIT and Stanford University TTOs, our setting has been the study context for other published research, which includes analysis of dynamic capabilities development using licensing and patent data from 1927 to 2002 (George, 2005), inductive case studies on building legitimacy for novel technologies and role-identity modification among scientists who commercialize their inventions (George & Bock, 2009; Jain & George, 2007; Jain, George, & Maltarich, 2009), and the influence of inventors' scientific-domain distance on licensing (Kotha, George, & Srikanth, 2013). However, our research examines new aspects of this study context for our main theory variables that have not been previously investigated or associated with published results. We chose this context and these data specifically because they allowed us to examine contracts between academia and industry partners to commercialize inventions with uncertain value. A technology-transfer license is a formal contract between the university and licensee that specifies the conditions by which the licensee can use the invention for commercial purposes. We analyze the contract payment structure—the specific terms regarding the upfront fixed-fee and performance-based royalty rate paid by the licensee as the "price" for using the technology.

Sample

Our sample consists of 964 invention-contract pairs (527 contracts for patented and 437 contracts for non-patented inventions) licensed from 1990 to 2002. Our sample also represents 427 inventions licensed through 472 contracts (314 single-invention licenses and 158 bundled-invention licenses). In our robustness analyses (discussed later), we ran additional models with the combined sample and for the bundled contracts and found results consistent with our main theory variable results.

Dependent Variables

Our study examined the following three dependent variables: *commercial success* of the licensed invention (to test Hypothesis 1), and the negotiated upfront *fixed-fee* payment and the *royalty rate* between a TTO and a licensee firm (to test Hypothesis 2–Hypothesis 5). The first dependent variable—commercial success—is the licensing revenue earned by the TTO from an invention. The second and third dependent variables are based on the payment structure. Licensing firms pay a fixed-fee payment to the TTO upon licensing the invention and royalties based on sales. Following standard procedures to correct for skewness, we used the natural log transformations of the dependent variables. For bundled contracts with multiple inventions, we divided the payments according to the contract allocation rules (most of them specified equal sharing). In our sample, the average revenue earned by an invention was $51,997 and the average fixed-fee payment was $12,025. The royalty rate is a percentage of annual sales based on the licensed invention. The average royalty rate was 1.63% of sales.

Independent Variables

We created the *licensing manager experience* (LME) variable by counting the number of prior contracts that were negotiated and signed by the focal licensing manager at the time of invention licensing (Faems et al., 2008; Vanneste & Puranam, 2010). To improve its interpretation, we rescaled the variable by dividing it by 10. We then formed three interaction variables based on the cross-product of the *licensing manager experience* (as a proxy for the *ability* to signal) variable with the following three explanatory variables (as proxies for the *need* to signal). First, the *science intensity* of an invention was based on the proportion of the number of backward citations to academic-scientific articles—out of the total number of backward citations (academic articles plus other patents)—in the invention's patent. When the proportion is high, it indicates that an invention is science-intensive, drawing less heavily from the applied-scientific knowledge associated with published patent domains. The inventions with high academic-science content are also early-stage technologies and difficult to transfer into practice (Bikard, 2014). They require the inventors' ongoing involvement before they can be realized into actual products or services, or the knowledge effectively transferred to licensee firms. Conversely, at lower proportions of academic-scientific to total backward citations, the inventions are likely to be at a later stage in the commercialization cycle. These inventions will require less ongoing involvement from inventors and less effort by licensing managers to match them to prospective licensees (Ziedonis, 2007). Second, *inventor experience* is measured by the average number of prior disclosed inventions among inventors. Third, *patent scope* was created based on "the number of sub-classes into which the United States Patent and Trademark Office (USPTO) assigns the patent" (Lerner, 1994: 320).

Control Variables

We accounted for several characteristics of the licensing manager, the inventor, the invention, and the licensee as control variables.

Licensing manager control variables. We controlled for the *number of unlicensed inventions* in a licensing manager's portfolio over the previous five years, as a large inventory of unlicensed inventions may pressure them to settle for less-than-favorable agreements. We also created variables to represent *positive performance* and *negative performance* relative to their own past performance and to other licensing managers. According to behavioral theory, licensing managers who perform relatively better now than in the past and relative to others may have different motivations behind their licensing terms than less successful managers. We used two spline variables to represent positive and negative licensing-manager performance (following Greve, 2003). We also included *licensing-manager fixed effects* to account for any other idiosyncratic, time-invariant unobserved factors that may be related to our dependent variables. During the sample period from 1990 to 2002, there were 11 licensing managers, each of whom specialized in a different scientific domain. As such, it was unnecessary to include additional domain fixed-effect variables.

Inventor control variables. In addition to inventor experience, we controlled for other characteristics of the invention team, which included the presence of *star scientists* on the team—an indicator variable (1 = yes) if at least one of the inventors on the project achieved this distinction—as determined based on their citations and research record[5]; the *number of inventors,* as larger teams may create more valuable inventions (Wuchty, Jones, & Uzzi, 2007) and may serve as an independent signal; and *prior collaboration*—the proportion of inventors who had worked together prior to the current invention—because these inventor teams have lower coordination costs (Kotha et al., 2013).

Invention control variables. We controlled for *invention quality* by counting the number of citations the technology's patent received until 2007 (excluding self-citations). This decision was based on Ziedonis (2007), who demonstrated that citation counts serve as a useful indicator of an invention's economic potential. We included an indicator variable to denote whether the invention resulted from *funded research* (1 = a private firm or government agency funded the research), as funded projects are likely to be of greater commercial interest to a sponsoring firm. We incorporated count variables for the number of times an invention has been *previously licensed* (and *previously licensed*^{2} to account for diminishing returns) and the *number of inventions* in a bundled contract. Inventor teams can work on de novo projects; however, it is more common for inventors to work on path-dependent technology trajectories (Dosi, 1982). Inventors who work within a given technology trajectory often have a rich history that propels them forward, whereas de novo projects present more risk. When an invention is disclosed to the TTO, the Intellectual Property-rights Manager (IPM) systematically asks whether the project is de novo or a continuation of an existing stream of research. We used an indicator variable to capture whether the project was a *continuing invention* (1 = yes).

Licensee control variables. In addition to our inventor and invention controls, we also controlled for several aspects of the licensee firms. For the *licensee-expertise* variable, we used the number of patents owned by the licensee on the agreement signing date. To verify the robustness of this measure, we examined the actual contract documents and correspondence between the licensee and the TTO. If the contract documents or development plans mentioned the licensee's expertise, we coded the variable as 1. Using this measure, we tested the mean difference in the number of patents and found that licensees with expertise owned 3.78 patents, whereas licensees without expertise owned 0.68. This difference was significant (p value < 0.001), and we found similar results using either measure. Licensees with ongoing relationships become recognized partners, unlike one-time participants in an arm's length transaction (Corts & Singh, 2004; Granovetter, 1985). To determine the *licensee-manager relationship history*, we counted the number of inventions the focal licensing manager had licensed to the firm prior to the current invention. To capture *licensee size*, we used an indicator variable

[5] To determine star-scientist status, we adapted Zucker and Darby's (1996) citation-based identification method and rationale. We relied on data from ISI's list of the top 250 scientists in 21 subject categories (www.isihighlycited.com). We manually matched this list to each inventor from our licensing data. Out of the 4,950 unique inventors in our sample, we identified 135 inventors as star scientists.

to capture the publicly listed company status (1 = yes) of the firm at the time of contract signing.[6] As most cutting-edge knowledge is not publicized and the inventors are often located near their university TTO licensors, we also controlled for the *licensee-TTO distance* (in miles between the university and the licensee firm's headquarters). For licensee firms with multiple locations, we checked the contract documents to identify the location where the invention's commercial development took place.

Estimation Strategy

To test Hypothesis 1, we used an ordinary least squares (OLS) estimation to predict the commercial success of an invention. To test Hypotheses 2–5, we used seemingly unrelated regression (SUR) to jointly predict the royalty rate and fixed payment amount in a contract simultaneously, as they could be related (Agarwal, Echambadi, Franco, & Sarkar, 2004; Wooldridge, 2002; Zellner, 1962). One advantage of using SUR estimations is that this technique properly accounts for correlated error terms in a set of equations such as ours, where the determination of fixed-fee payments and royalty rates occurs jointly. Furthermore, not all of the inventions in the TTO's portfolio are licensed, and there may be unobserved factors that may cause an invention to be licensed, influence contract payment structures, and be correlated with licensing manager's experience. To account for these conditions, we implemented a simple sample selection correction (Hamilton & Nickerson, 2003) and use the sample selection hazard in all estimations of contract payment structures as an additional control variable.

RESULTS

We report our summary statistics and correlations in Table 1 for the sample of inventions disclosed to the TTO. All correlations that equal 0.064 and above are significant at a p value < 0.05.

In our control Model 1 (Table 2), we report the OLS regression estimation results predicting the commercial success of an invention. In Model 2, we introduce licensing manager experience (LME) to test the Hypothesis 1 that, *ceteris paribus*, LME will be positively related to the income earned by an invention. We find support for Hypothesis 1 (Model 2; $\beta = 0.09$; $p = 0.052$) in the full sample and similar results in the patented sample (Model 3; $\beta = 0.10$; $p = 0.119$). As LME increases from one standard deviation (*SD*) below the mean value to one *SD* above, the income earned by an invention increases by 207% (from $1,796 to $3,711). This confirms our prediction that LME experience matters for commercial success. We proceed to our next set of hypotheses to analyze more specifically how experience matters for constructing contract payment structures.

In Table 3, we report the SUR estimations to predict the fixed-fee payments and royalty rates for the patented sample. In Model 1, we present only the controls and LME variables. Before we discuss the tests of the hypotheses, it is worth highlighting a few results concerning the control variables to explore to what extent conventional bargaining explanations apply to our predictions.

For ease of exposition, we focus on contrasting bargaining and signaling explanations for several control variables that are significant predictors of both fixed-fee payments and royalty rates. First, we examine licensee size. From a bargaining perspective, a larger licensee, who has more power, would pay lower fixed-fees *and* royalty rates. From a signaling perspective, there would be less need to send a signal to a well-resourced licensee that could presumably use its resources to conduct a thorough analysis of the invention being proposed. Thus, signaling theory also predicts that as licensee size increases, the licensee can more effectively discern the potential value created by the licensing manager. Therefore, the licensing manager does not have to send as strong a signal and can design a contract structure with a higher fixed-fee payment ($\beta = 1.20$; $p < 0.001$) and lower royalty rate ($\beta = -0.27$; $p < 0.001$). These results for licensee size are consistent with the signaling explanation. Second, we review the results for geographic distance. A bargaining perspective would suggest that it would be easier to bargain over short distances, so we would expect both royalty rates *and* the upfront payment to decrease with greater distance. A signaling perspective would suggest that matching is more difficult with distance; thus, less value is created, and the licensing manager offers a correspondingly weaker signal (higher upfront payment $\beta = 0.36$; $p < 0.001$; lower royalty rate $\beta = -0.03$; $p = 0.02$) for geographically distant licensees. This is what we in fact observe. Third, from the signaling theory perspective, we argue there will be greater information asymmetry associated with science-intensive inventions, inventor experience, and inventions with wide potential

[6] For a subset of our sample, we also measured licensee size based on the number of employees of the company; this yielded similar results for the theory variables.

TABLE 1
Summary Statistics and Correlations

Variables	Mean	*SD*	1	2	3	4	5	6	7
Commercial success (ln)	7.86	3.70	1						
Fixed payment (ln)	6.42	3.71	.34	1					
Royalty rate (ln)	0.62	0.71	−.16	−.16	1				
Not patented	0.45	0.50	−.12	−.22	.05	1			
Science intensity	0.42	0.38	.09	.21	.06	−.53	1		
Inventor experience	1.85	1.05	−.02	.09	.06	−.15	−.01	1	
Patent scope	0.65	0.53	.11	.24	.07	−.57	.68	.14	1
Unlicensed inventions	28.00	23.99	−.10	.10	.04	.02	.04	.13	.05
Positive performance	0.04	0.08	−.20	−.11	.19	.04	−.04	.01	−.04
Negative performance	−0.01	0.02	−.11	−.11	.07	.05	.05	.07	.03
Star scientist	0.22	0.41	.04	.11	−.07	−.29	.40	.28	.31
Number of inventors	3.09	2.26	−.01	−.09	.10	.16	−.09	.17	−.16
Prior collaboration	0.50	0.45	−.05	−.10	−.06	−.08	.01	.49	.06
Invention quality	13.63	21.15	.10	.13	−.22	−.58	.21	.09	.23
Funded research	0.62	0.49	−.14	−.13	.12	.20	−.15	−.10	−.20
Previously licensed	6.73	7.52	−.01	−.10	−.45	.11	−.13	−.12	−.26
Number of inventions	5.01	5.13	−.05	−.02	−.01	−.20	.11	.57	.21
Continuing invention	0.53	0.50	.05	.26	.03	−.29	.34	.11	.46
Licensee expertise	2.83	2.94	.30	.37	−.33	−.15	.11	.11	.16
Licensee–manager relationship	0.18	0.38	−.12	−.20	.03	.10	−.06	.03	−.15
Licensee size	0.30	0.46	.22	.22	−.25	−.03	.05	.01	.00
Licensee–TTO dist. ('000km)	1.45	1.88	.13	.24	−.16	−.03	.04	−.01	−.03
Licensing manager experience	46.63	40.07	−.05	.03	.07	−.01	.08	.35	.09

patent classes. Therefore, these inventions should be associated with stronger signals. Results support the predictions of the signaling theory.

In Hypothesis 2, we predicted the direct main effect of LME on the two contract terms: a *negative* relationship with the amount of fixed-fee upfront payment and a *positive* relationship with the size of the royalty rate. The results are consistent with our predictions (shown in Model 1). LME is negatively related to upfront payments ($\beta = -0.17$; $p = 0.04$; note that the fixed-fee payment variable has been transformed as a natural log). As LME increases from 1 *SD* below the mean value to 1 *SD* above, the fixed amount decreases by 17% (from 7.91 to 6.55; see Figure 1a). On the other hand, the negotiated royalty rate increases with LME ($\beta = 0.02$; $p = 0.04$). As LME increases to 1 *SD* above the mean, the royalty rate increases from 1.62% of sales to 1.97%, an increase of 22% (see Figure 1b).

In Hypothesis 3, we predicted that as inventions become more science intensive, the direct relationship between LME and the two contract terms would magnify, showing larger decreases in upfront fixed-fee payments (Hypothesis 3a) and larger increases in royalty rates (Hypothesis 3b). We observe results consistent with these predictions (shown in Model 2 and plotted in Figures 2a and 2b). For science-intensive inventions, the original direct and negative LME-fixed-fee relationship intensifies ($\beta = -0.32$; $p = 0.02$). As LME increases from mean −1 *SD* to mean +1, the upfront fixed-fee payment for science-intensive inventions decreases from 7.88 to 6.15 (22%). However, for low science-intensive inventions, the upfront fixed-fee payment increases from 8.04 to 8.25 for the same change in LME. In regards to royalty rates for science-intensive inventions, the original direct and positive LME-royalty rate relationship intensifies ($\beta = 0.05$; $p = 0.005$). As LME increases from mean −1 *SD* to mean +1, the royalty payments for science-intensive inventions increase from 1.65% to 2.12, an increase of over 28%. However, for low science-intensive inventions, the royalty rate decreases from 1.54% to 1.44—a decrease of 6%—for the same change in LME. Hypothesis 3 is also supported in the full model with all the interactions (see Model 5).

In Hypothesis 4, we predicted that as LME increases, the direct relationship between LME and the two contract terms would magnify for inventions by experienced inventors, with the upfront fixed-fee payment decreasing (Hypothesis 4a), and the royalty rate increasing (Hypothesis 4b) at more noticeable levels. We find results consistent with these predictions when we examine the betas of the interactions (Model 3 and plotted in Figures 3a and 3b).

TABLE 1
(Continued)

8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1														
−.28	1													
.09	.21	1												
.08	−.08	.02	1											
−.02	.32	−.02	−.05	1										
.05	.04	.08	.28	.12	1									
−.05	−.08	−.13	.29	−.13	.14	1								
.06	−.06	.13	−.26	−.07	−.03	−.29	1							
.00	−.16	.00	.11	.06	.07	.13	.04	1						
.12	.01	.10	.44	.03	.39	.14	−.16	−.10	1					
−.01	−.01	.04	.11	−.16	.10	.20	−.16	−.20	.09	1				
.01	−.09	−.11	.05	−.06	−.01	.17	−.17	.00	.11	.15	1			
.10	−.02	.06	.01	.02	.06	−.04	.07	.08	−.05	−.17	−.03	1		
.04	−.02	.00	−.02	−.06	−.04	.08	−.06	.09	.09	.03	.54	−.04	1	
.04	−.18	−.19	.10	−.04	−.08	.06	−.08	.21	−.12	−.05	.15	.01	.12	1
.65	−.29	.07	.33	.01	.24	−.03	.01	−.04	.39	−.06	−.10	.16	−.07	.05

Note: $n = 964$ observations; all values of 0.064 and above are significant at $p < 0.05$.

For inventions by experienced inventors, the original direct and negative LME-fixed-fee relationship strengthens ($\beta = -0.09$; $p = 0.02$). As LME increases from mean −1 *SD* to mean +1, the upfront fixed-fee payment for inventions by experienced inventors decreases from 8.07 to 5.13, a decrease of 36%. However, for inventions by inventors without experience, the fixed upfront payment decreases from 8.10 to 7.69—a decrease of 5%—for the same change in LME. The original direct and positive LME-royalty rate relationship similarly strengthens ($\beta = 0.01$; $p = 0.01$). As LME increases, the royalty payment for inventions by experienced inventors increases from 1.93% to 2.97. For inventions by inventors without experience, the royalty payment increases from 1.38% to 1.45 for the same change in LME. Due to multi-collinearity in the full model, only the fixed-payment coefficient is statistically significant ($p = 0.03$).

In Hypothesis 5, we predicted that for widely applicable inventions (wide patent scope), the direct relationship between LME and the two contract terms would magnify, displaying more pronounced decreases in upfront fixed-fee payments (Hypothesis 5a) and increases in royalty rates (Hypothesis 5b). We find results fully consistent with these predictions (shown in Model 4 and Figures 4a and 4b). We observe a negative and significant effect for the interaction term on fixed upfront payments (Hypothesis 5a: $\beta = -0.18$; $p = 0.07$). As LME increases from mean −1 *SD* to mean +1, the upfront fixed-fee payment for widely applicable inventions decreases from 7.70 to 5.93—a decrease of 23%. For more narrowly defined inventions (mean −1 *SD*), the upfront fixed-fee payment decreases from 8.12 to 7.30—a decrease of only 10%—for the same change in LME. In addition, for widely applicable inventions, the original direct and positive LME-royalty rate relationship intensifies ($\beta = 0.08$; $p = 0.000$). As LME increases from mean −1 *SD* to mean +1, the royalty payments for widely applicable inventions increase from 1.52% to 2.20, an increase of nearly 45%. For more narrow inventions, the royalty rate marginally decreases from 1.73% to 1.67 for the same change in LME. Due to multi-collinearity in the full model, only the royalty-rate coefficient is statistically significant ($p < 0.001$).

Robustness Checks

We conducted a series of robustness checks to verify our findings. In the first set of analyses, we

TABLE 2
OLS Estimations of Commercial Success of an Invention

	Full Sample		Patented Sample
	(1)	(2)	(3)
Science intensity	−0.49 (0.53)	−0.55 (0.52)	−1.39** (0.67)
Inventor experience	−0.08 (0.19)	−0.06 (0.19)	0.19 (0.24)
Patent scope	0.50 (0.34)	0.52 (0.34)	−0.10 (0.41)
Unlicensed inventions	−0.01** (0.01)	−0.02*** (0.01)	−0.03** (0.01)
Positive performance	−12.68*** (2.49)	−12.16*** (2.44)	−19.32*** (3.55)
Negative performance	4.31 (7.82)	4.95 (7.86)	1.82 (11.62)
Star scientist	0.44 (0.36)	0.36 (0.36)	0.13 (0.47)
Number of inventors	0.16*** (0.05)	0.16*** (0.05)	0.27*** (0.07)
Prior collaboration	−0.20 (0.32)	−0.22 (0.32)	−0.10 (0.36)
Invention quality	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Funded research	−0.80*** (0.29)	−0.80*** (0.29)	−0.77** (0.31)
Previously licensed	−1.89** (0.84)	−1.88** (0.84)	−0.12 (1.61)
Previously licensed squared	0.34 (0.22)	0.34 (0.22)	−0.03(0.45)
Number of inventions	−0.17 (0.27)	−0.20 (0.27)	−0.75** (0.35)
Continuing invention	0.22 (0.29)	0.29 (0.30)	0.33 (0.32)
Licensee expertise	0.00** (0.00)	0.00** (0.00)	0.00 (0.00)
Licensee–Manager relationship	−0.41* (0.23)	−0.45** (0.23)	0.25 (0.45)
Licensee size	0.82*** (0.25)	0.81*** (0.26)	0.87*** (0.31)
Licensee–TTO distance ('000km)	0.03 (0.07)	0.02 (0.07)	0.06 (0.09)
LME (H1)		**0.09* (0.05)**	**0.10† (0.07)**
Constant	11.26*** (1.11)	10.90*** (1.13)	10.64*** (1.64)
R^2	0.29	0.29	.31

Notes: Clustered standard errors in parentheses. Licensing-manager and year fixed-effects are included but not reported to conserve space. The dependent variable is revenue earned (ln) until the end of the sample window. Full sample $N = 964$ and patented sample $n = 527$.

† = 0.119

* $p < 0.10$

** $p < 0.05$

*** $p < 0.01$ (two-tailed test)

employ new decision variables to validate the selection and matching mechanism for the interaction hypotheses. Second, we examined signaling theory predictions in the full sample of inventions consisting of patented and non-patented inventions. Third, we confirmed that the signaling theory predictions also hold at the contract level. Fourth, we examined what type of licensing manager experience is most important in determining contract terms. Fifth, we contrasted the experience of licensing managers, inventors, and licensees to see whose experience best explains the choice of contract terms.

Additional analyses to validate selection and matching mechanisms. We conducted further analyses to validate our selection and matching mechanisms as the drivers for experience. To accomplish this, we formed two new dependent variables (DVs), one to test for selection and the other to test for matching, to use in the post-hoc analysis. We reran our analyses using these DVs. If we observed statistically significant results for our theory variables with these DVs, we inferred that the selection and matching mechanisms were operating as expected in our predictions (summarized in Table 4).

To test the selection mechanism: we constructed a new variable identifying *inventions selected for commercialization*. In our view, this variable offers a direct test about whether licensing managers assigned to an invention become more selective (i.e., less likely to select an invention for commercialization) as their experience increases. Our prediction for this post-hoc analysis is that as LME increases, the likelihood that a given invention will be accepted for commercialization will decrease as a result of being more selective about which inventions they attempt to commercialize. We formed a sample of 1,967 inventions disclosed to the TTO in the sample window and used it to test if LME is negatively related to selection probability. This dependent variable is binary (1 = TTO selected invention for initial commercialization efforts, otherwise 0). Once an invention is disclosed to the TTO, an intellectual property manager and a licensing manager are assigned to the invention.

TABLE 3
SUR Estimations with Licensing Manager Fixed Effects of Fixed Payment (ln) and Royalty Rate (ln)

	(1)		(2)	
	Fixed	**Royalty**	**Fixed**	**Royalty**
Sample selection hazard	5.12** (2.09)	−0.57* (0.30)	5.05** (2.08)	−0.56* (0.29)
Science intensity	−1.30** (0.60)	0.27*** (0.08)	−1.36** (0.50)	0.28*** (0.08)
Inventor experience	−0.25 (0.34)	0.13*** (0.05)	−0.30 (0.33)	0.14*** (0.05)
Patent scope	−1.56*** (0.49)	0.20*** (0.07)	−1.56*** (0.49)	0.20*** (0.07)
Unlicensed inventions	−0.02 (0.01)	0.01*** (0.00)	−0.01 (0.01)	0.00** (0.00)
Positive performance	5.86* (3.01)	1.61*** (0.42)	6.19** (3.00)	1.56*** (0.42)
Negative performance	−27.82*** (9.22)	−1.68 (1.30)	−31.59*** (9.31)	−1.05 (1.31)
Star scientist	1.74** (0.68)	−0.03 (0.10)	1.66** (0.68)	−0.02 (0.09)
Number of inventors	0.40*** (0.12)	−0.09*** (0.02)	0.39*** (0.12)	−0.09*** (0.02)
Prior collaboration	−0.24 (0.40)	−0.13** (0.06)	−0.21 (0.40)	−0.13** (0.06)
Invention quality	−0.01 (0.01)	−0.00 (0.00)	−0.01 (0.01)	−0.00 (0.00)
Funded research	0.02 (0.30)	−0.03 (0.04)	0.11 (0.30)	−0.05 (0.04)
Previously licensed	1.19 (1.20)	−1.41*** (0.17)	1.44 (1.19)	−1.45*** (0.17)
Previously licensed squared	−0.29 (0.33)	0.24*** (0.05)	−0.37 (0.33)	0.25*** (0.05)
Number of inventions	−0.95*** (0.31)	−0.02 (0.04)	−0.75** (0.32)	−0.05 (0.05)
Continuing invention	1.66** (0.71)	−0.08 (0.10)	1.62** (0.71)	−0.07 (0.10)
Licensee expertise	0.00* (0.00)	−0.00 (0.00)	0.00* (0.00)	−0.00 (0.00)
Licensee–Manager relationship	−0.62** (0.27)	0.06 (0.04)	−0.57** (0.27)	0.05 (0.04)
Licensee size	1.20*** (0.33)	−0.27*** (0.05)	1.18*** (0.33)	−0.27*** (0.05)
Licensee–TTO distance (‘000km)	0.36*** (0.08)	−0.03** (0.01)	0.33*** (0.08)	−0.02** (0.01)
Licensing Manager Experience (LME) (H2)	**–0.17** (0.08)**	**0.02** (0.01)**	0.04 (0.12)	−0.01 (0.02)
LME × Science intensity (Hypothesis 3)			**–0.32** (0.14)**	**0.05*** (0.02)**
LME × Inventor experience (Hypothesis 4)				
LME × Patent scope (Hypothesis 5)				
Constant	2.19 (3.54)	2.83*** (0.50)	1.09 (3.55)	3.02*** (0.50)
Pseudo				
R^2	0.24	0.59	0.24	0.60
χ^2	147.10	690.39	154.26	709.78
Log likelihood	−1409.26		−1403.50	

Approximately once a month, the TTO's management team evaluates which inventions to commercialize by filing patents and evaluating licensing opportunities. These are the first steps in the commercialization process. We used this DV as a test of the mechanism of Hypothesis 2 and of Hypothesis 4. Both tests yielded results supporting a selection mechanism: experienced licensing managers select fewer inventions for commercialization ($\beta = -0.84$; $p < 0.001$) but limit their selectivity when it comes to inventions by experienced inventors ($\beta = 0.07$; $p < 0.001$). Unfortunately, we could not use this DV as a test for Hypothesis 3 (science-intensive inventions) and Hypothesis 5 (patent scope) because the inventions that are not selected for commercialization are also not patented, which is a feature we required to test for the selection mechanism related to these two predictions (the two moderators depend on having patent information for the inventions).

To test the matching mechanism: we constructed another variable identifying *exclusive licensing of an invention*. This second variable was also binary (1 = exclusively licensed). If an invention is licensed exclusively, the TTO is exposed to the risk of the licensees shelving the technology as a competitive tactic (Dechenaux, Thursby, & Thursby, 2009). Unless the licensing manager is assured of the licensee's market intentions and can trust their actions, the licensing manager is less likely to agree to an exclusive license. As LME increases, we expect that their experience enables them to match inventions with the best licensee who will use its exclusive agreement productively and will make substantial investments to commercialize, rather than shelve, the invention. Less experienced managers are not as confident in their matching abilities and would be less likely to sign an exclusive agreement. We found results for a direct relationship (as a test of Hypothesis 2), as the probability of signing an exclusive agreement increases with LME ($\beta = 0.02$; $p = 0.02$). The probability of signing an exclusive agreement increases even more for science-intensive inventions

TABLE 3
(Continued)

(3)		(4)		(5)	
Fixed	Royalty	Fixed	Royalty	Fixed	Royalty
6.45*** (2.16)	−0.77** (0.30)	4.84** (2.09)	−0.45 (0.29)	6.20*** (2.17)	−0.56* (0.30)
−1.36** (0.59)	0.28*** (0.08)	−1.15* (0.60)	0.20** (0.08)	−0.04 (0.81)	0.07 (0.11)
0.05 (0.36)	0.09* (0.05)	−0.21 (0.33)	0.12*** (0.05)	0.00 (0.36)	0.10** (0.05)
−1.36*** (0.50)	0.17** (0.07)	−0.52 (0.76)	−0.25** (0.10)	−0.92 (0.77)	−0.21** (0.11)
−0.03* (0.02)	0.01*** (0.00)	−0.01 (0.01)	0.00** (0.00)	−0.02 (0.02)	0.00** (0.00)
6.55** (3.01)	1.51*** (0.42)	6.24** (3.01)	1.45*** (0.41)	7.00** (3.00)	1.38*** (0.41)
−31.19*** (9.29)	−1.18 (1.31)	−30.77*** (9.34)	−0.40 (1.28)	−35.94*** (9.42)	0.12 (1.29)
2.24*** (0.71)	−0.11 (0.10)	1.72** (0.68)	−0.02 (0.09)	2.14*** (0.71)	−0.06 (0.10)
0.46*** (0.13)	−0.10*** (0.02)	0.39*** (0.12)	−0.09*** (0.02)	0.44*** (0.13)	−0.09*** (0.02)
−0.38 (0.41)	−0.10* (0.06)	−0.11 (0.41)	−0.18*** (0.06)	−0.29 (0.41)	−0.17*** (0.06)
−0.01 (0.01)	−0.00 (0.00)	−0.01 (0.01)	−0.00 (0.00)	−0.01 (0.01)	−0.00 (0.00)
−0.02 (0.30)	−0.03 (0.04)	0.11 (0.31)	−0.07 (0.04)	0.10 (0.31)	−0.07 (0.04)
1.62 (1.20)	−1.47*** (0.17)	1.22 (1.19)	−1.42*** (0.16)	1.86 (1.20)	−1.48*** (0.17)
−0.40 (0.33)	0.25*** (0.05)	−0.32 (0.33)	0.25*** (0.05)	−0.49 (0.33)	0.27*** (0.05)
−0.89*** (0.31)	−0.03 (0.04)	−0.94*** (0.31)	−0.03 (0.04)	−0.69** (0.32)	−0.05 (0.04)
2.11*** (0.73)	−0.15 (0.10)	1.44** (0.72)	0.02 (0.10)	1.95*** (0.75)	−0.02 (0.10)
0.00* (0.00)	−0.00 (0.00)	0.00* (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
−0.60** (0.27)	0.06 (0.04)	−0.60** (0.27)	0.06 (0.04)	−0.55** (0.27)	0.05 (0.04)
1.25*** (0.33)	−0.28*** (0.05)	1.23*** (0.33)	−0.28*** (0.04)	1.25*** (0.32)	−0.28*** (0.04)
0.39*** (0.08)	−0.03*** (0.01)	0.35*** (0.08)	−0.02** (0.01)	0.36*** (0.08)	−0.02** (0.01)
−0.00 (0.11)	−0.00 (0.02)	0.01 (0.13)	−0.05*** (0.02)	0.27* (0.16)	−0.08*** (0.02)
				−0.31** (0.14)	0.04* (0.02)
−0.09** (0.04)	0.01** (0.01)			−0.09** (0.04)	0.01‡ (0.01)
		−0.18* (0.10)	0.08*** (0.01)	−0.08 (0.11)	0.07*** (0.01)
−0.97 (3.78)	3.31*** (0.53)	1.37 (3.56)	3.20*** (0.49)	−2.25 (3.79)	3.52*** (0.52)
0.24	0.60	0.24	0.62	0.25	0.62
154.02	705.18	151.33	770.59	162.68	782.93
−1404.40		−1392.99		−1387.14	

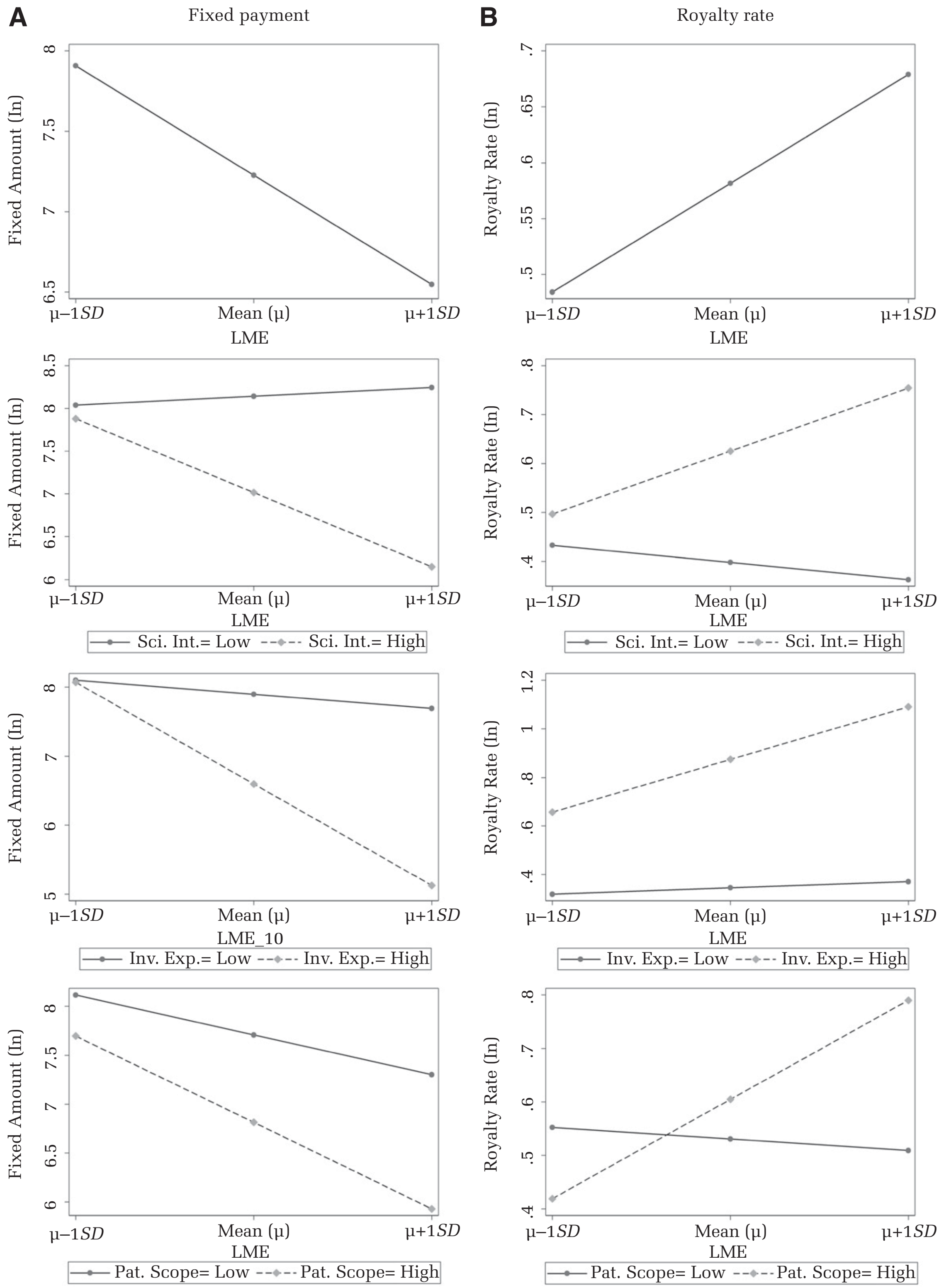
Note: Standard errors in parentheses. All estimations include sample selection hazard to control for unobserved effects leading to licensing and contract structure. Licensing-manager fixed effects are included but not reported to conserve space. $n = 527$ (patented sample).

‡ $p = 0.198$
* $p < 0.10$
** $p < 0.05$
*** $p < 0.01$ (two-tailed test)

(β = 0.04; $p = 0.01$) and inventions with a broad patent scope (β = 0.06; $p < 0.001$), indicating the greater impact of improved matching. We use this as evidence in support of the matching mechanism at work for these predictions. Consistent with our prediction, the post-hoc test for the matching mechanism was not significant for inventor experience (β = 0.01; $p = 0.26$).

We also ran our original models (DV = contract payment structure components) once more with another independent variable to further explore the matching mechanism. When an invention is licensed to licensees with whom they have a prior relationship, the licensing manager's ability to effectively *match* the invention to the appropriate licensee is enhanced. We counted the prior licensing contracts between the licensee and either the inventor or the licensing manager. *Prior relationship ratio* is the proportion of prior relationships between the licensee and licensing manager out of all prior licensing contracts involving either party. In this situation, the licensee's scientific and technical capabilities are well known to the licensing manager. Consequently, for a given level of experience, licensing managers will secure a better match for a licensee with whom they have a prior relationship than they would otherwise. More value is thus created in repeat licensing relationships, and the licensing manager sends a stronger signal. Consistent with this reasoning, we find that as LME and prior

FIGURES 1–4
Interaction Plots of Experience and Payment Structure



Notes: These plots are based on results from Table 3 (Model 1: Hypothesis 2, Model 2: Hypothesis 3, Model 3: Hypothesis 4, Model 4: Hypothesis 5). *X*-axis values range from –1 *SD* to mean to +1 *SD*. *Y*-axis values are fixed payment (ln) and royalty rate (ln), respectively.

TABLE 4
Summary of Post-hoc Analysis of Hypothesis 2–Hypothesis 5

	Main Hypothesis Test	Post-hoc Analysis		
	Signal (decreasing upfront fixed payment and increasing royalty)	Mechanism 1: Selection (DV proxy: Invention accepted for commercialization)	Mechanism 2: Matching (DV proxy: Exclusive license)	Remarks
Hypothesis 2: Licensing Manager Experience (LME)	**Supported**	**Present** (more selective with experience) (β = 0.84; $p < 0.001$)	**Present** (more confident of matching so more likely to sign exclusive license) (β = 0.02; $p = 0.02$)	Support for H1 (higher licensing income) also confirms that LM experience leads to value creation and not over confidence.
Hypothesis 3: Science-intensity × LME	**Supported**	Can't be tested since non-commercialized inventions are also not patented	**Present** (LME with higher experience are more likely to science heavy inventions to exclusive licensee) (β = 0.04; $p = 0.01$)	
Hypothesis 4: Inventor experience × LME	**Supported**	**Present** (as LME and inventor experience both increase) (β = 0.07; $p <$ 0.001)	Not present as posited by us (LME and inventor experience are not complements for matching proxy) (β = 0.01; $p = 0.26$)	We argued for only the selection mechanism for this hypothesis and find evidence consistent with our arguments.
Hypothesis 5: Patent scope × LME	**Supported**	Can't be tested since non-commercialized inventions are also not patented	**Present** (LM with higher experience are more likely to take inventions with wide applicability to exclusive licensee (β = 0.06; $p < 0.001$)	We argued for only the matching mechanism for this hypothesis and find evidence consistent with our arguments.

Notes: By "present," we mean that our post-hoc analyses revealed evidence in support of the arguments for selection or matching in our predictions.

relationships increase, reduced upfront fixed-fee payments (see Table 5; β = −0.32; $p = 0.02$) and increased royalty-rates (see Table 5; β = 0.05; $p = 0.02$) occur at an increasing rate.

Full sample. Similar to the licensed-invention portfolios of other TTOs, our sample contained a mixture of patented (55% of the total) and unpatented inventions. As mentioned earlier, our main analyses focused only on the patented and licensed inventions, as these provided us with additional information about invention quality and a variety of other economically relevant characteristics (Shane, 2002). But in this robustness check, we re-ran our models on the combined sample of inventions. We included an additional control variable to indicate whether an invention was unpatented and set the patent based control in the unpatented sample to zero. In this sample, using the same variables as in the full sample, we found results similar to our main results based only on the patented inventions (see Table 5).

Results at the contract level. Our main analyses were at the individual-invention level to examine the signaling-need mechanism at the most detailed level. Since some inventions were licensed together as bundles, we re-ran our models at the bundled-contract level. To ensure robustness at this level, in the patented sample we constructed aggregate variables by using the median values of the invention's science intensity, inventor experience, patent scope, and prior relationship ratio within an agreement. (These variables for single-invention contracts retained their original values.) We found consistent results for licensing manager experience, inventor experience, patent scope, and prior relationships variables.

Licensing experience or failure experience. It is possible that licensing managers may also learn from

TABLE 5
Additional Analyses (Patented Sample) and Robustness Checks (Full Sample)

Model	Patented sample		Full sample					
	(1)		(2)		(3)		(4)	
	Fixed	Royalty	Fixed	Royalty	Fixed	Royalty	Fixed	Royalty
Sample selection hazard	3.99** (1.97)	−0.55* (0.28)	4.71*** (1.77)	−0.32 (0.27)	4.63*** (1.77)	−0.31 (0.27)	5.35*** (1.81)	−0.51* (0.27)
Not patented	n.a.	n.a.	−0.24 (0.43)	−0.04 (0.06)	−0.26 (0.43)	−0.03 (0.06)	−0.28 (0.43)	−0.02 (0.06)
Science intensity	−1.27** (0.59)	0.33*** (0.09)	−1.07** (0.51)	0.28*** (0.08)	−1.15** (0.51)	0.29*** (0.08)	−1.10** (0.51)	0.29*** (0.08)
Inventor experience	−0.17 (0.33)	0.16*** (0.05)	−0.27 (0.28)	0.11** (0.04)	−0.30 (0.29)	0.11*** (0.04)	−0.07 (0.31)	0.05 (0.05)
Patent scope	−1.60*** (0.48)	0.17** (0.07)	−1.57*** (0.42)	0.13** (0.06)	−1.59*** (0.42)	0.13** (0.06)	−1.49*** (0.42)	0.10 (0.06)
Unlicensed inventions	0.00 (0.01)	0.00** (0.00)	0.01 (0.01)	0.00 (0.00)	0.01 (0.01)	0.00 (0.00)	0.01 (0.01)	0.00** (0.00)
Positive performance	6.57** (3.24)	1.51*** (0.47)	8.02*** (3.00)	1.42*** (0.45)	7.55** (3.00)	1.50*** (0.45)	8.85*** (3.03)	1.17*** (0.45)
Negative performance	−35.39*** (10.03)	0.81 (1.45)	−34.60*** (9.41)	−0.56 (1.41)	−35.30*** (9.40)	−0.48 (1.41)	−38.00*** (9.61)	0.45 (1.43)
Star scientist	1.42** (0.64)	0.05 (0.09)	1.56*** (0.59)	0.07 (0.09)	1.54*** (0.58)	0.08 (0.09)	1.84*** (0.61)	−0.01 (0.09)
Number of inventors	0.38*** (0.12)	−0.10*** (0.02)	0.40*** (0.11)	−0.08*** (0.02)	0.41*** (0.11)	−0.08*** (0.02)	0.43*** (0.11)	−0.09*** (0.02)
Prior collaboration	−0.21 (0.41)	−0.15** (0.06)	−0.26 (0.36)	−0.16*** (0.05)	−0.20 (0.36)	−0.17*** (0.05)	−0.35 (0.36)	−0.13** (0.05)
Invention quality	−0.10 (0.14)	0.01 (0.02)	−0.12 (0.13)	−0.00 (0.02)	−0.11 (0.13)	−0.00 (0.02)	−0.13 (0.13)	0.00 (0.02)
Funded research	0.02 (0.30)	−0.03 (0.04)	−0.09 (0.27)	−0.03 (0.04)	−0.12 (0.27)	−0.03 (0.04)	−0.11 (0.27)	−0.03 (0.04)
Previously licensed	0.09 (0.14)	−0.22*** (0.02)	0.18 (0.12)	−0.20*** (0.02)	0.17 (0.12)	−0.20*** (0.02)	0.21* (0.12)	−0.21*** (0.02)
Previously licensed squared	−0.00 (0.01)	0.01*** (0.00)	−0.01 (0.01)	0.01*** (0.00)	−0.01 (0.01)	0.01*** (0.00)	−0.01* (0.01)	0.01*** (0.00)
Number of inventions	−0.72** (0.31)	−0.09* (0.04)	−0.95*** (0.26)	−0.07* (0.04)	−0.86*** (0.26)	−0.08** (0.04)	−0.92*** (0.26)	−0.08** (0.04)
Continuing invention	1.29* (0.66)	−0.06 (0.10)	1.43** (0.61)	0.02 (0.09)	1.43** (0.61)	0.03 (0.09)	1.65*** (0.62)	−0.04 (0.09)
Licensee expertise	0.00* (0.00)	−0.00 (0.00)	0.00*** (0.00)	−0.00 (0.00)	0.00*** (0.00)	−0.00 (0.00)	0.00*** (0.00)	−0.00 (0.00)
Licensee–Manager relationship	−1.27** (0.54)	0.14* (0.08)	−0.62** (0.25)	0.08** (0.04)	−0.91* (0.51)	0.14* (0.08)	−0.62** (0.25)	0.07** (0.04)
Licensee size	1.00*** (0.33)	−0.24*** (0.05)	1.08*** (0.28)	−0.29*** (0.04)	0.99*** (0.29)	−0.27*** (0.04)	1.10*** (0.28)	−0.29*** (0.04)
Licensee–TTO distance ('000km)	0.36*** (0.08)	−0.02** (0.01)	0.32*** (0.07)	−0.03*** (0.01)	0.33*** (0.07)	−0.03*** (0.01)	0.34*** (0.07)	−0.03*** (0.01)
Licensing manager experience (LME)	−0.14 (0.10)	0.02 (0.01)	**−0.23** (0.09)**	**0.02* (0.01)**	−0.19** (0.09)	0.02 (0.01)	−0.13 (0.11)	−0.01 (0.02)
Prior relationship ratio	2.98*** (1.09)	−0.40** (0.16)			1.73* (0.98)	−0.28* (0.15)		
LME * Prior relationship ratio	**−0.32** (0.13)**	**0.05** (0.02)**			**−0.22* (0.12)**	**0.03† (0.02)**		
LME * Inventor experience							**−0.06* (0.03)**	**0.02*** (0.00)**
Constant	3.36 (3.43)	2.24*** (0.49)	2.05 (3.13)	1.89*** (0.47)	1.90 (3.13)	1.90*** (0.47)	0.33 (3.29)	2.40*** (0.49)
Pseudo								
R^2	0.24	0.58	0.25	0.54	0.26	0.54	0.26	0.24
χ^2	154.09	651.44	208.34	714.04	214.54	724.13	212.11	154.09
Log likelihood	−1416.40		−1840.42		−1836.48		−1834.20	−1416.40

Notes: Standard errors in parentheses. All estimations include sample selection hazard to control for unobserved effects leading to licensing and contract structure. Licensing-manager fixed effects included but not reported to conserve space. Patented sample $n = 527$ and full sample $n = 964$.

† $p = 0.104$
* $p < 0.10$
** $p < 0.05$
*** $p < 0.01$

unsuccessful attempts at licensing (Zheng, Miner, & George, 2013). While we do not have comprehensive data on unsuccessful attempts at licensing, we do have information on all the inventions in the licensing managers' portfolios. To the extent that licensing managers attempted to license and were unsuccessful, the unlicensed inventions in their portfolios could also influence their learning. While we control for this stock of unlicensed inventions in the licensing managers' portfolios in all our estimations and robustness analyses, here we attempt to explore if the licensing managers also learned from the unlicensed inventions in their portfolios. We did not find any support that this form of learning better equipped licensing managers to signal in line with our predictions. Prior work with unlicensed inventions does not appear to improve the selection of potential technologies, or matching them to promising licensees as reflected by the signals we have defined.

Whose experience: Inventor's, licensing manager's, or the organization's? To the extent that licensing managers rely on inventors, inventor experience may be more important than licensing manager experience for signaling. Therefore, we repeat the estimations in Table 3, Models 2–5, by using inventor experience in place of LME. We do not find similar results to our main findings. Similarly, we replaced LME with the TTO organization's licensing experience in a domain. In these models, we find weak but statistically significant results for our theory variables. Both of these robustness tests confirm that LME with actual *licensing* is most strongly associated with signaling.

In summary, our robustness checks supported our hypotheses and predicted that licensing managers improve their ability to signal as they gain experience. In addition, we also took steps to confirm that it is the licensing managers' experience and not the inventor or the organization's experience that is most important for signaling. Furthermore, the extension to signaling theory that we have developed in this paper is a robust framework in our context and can explain many contingencies in the selection of a licensing deal structure.

DISCUSSION

Our study investigated the relationship between LME and the contract payment structure for a sample of over 950 licensing contracts from a TTO at a large U.S. university. To summarize our key findings: LME is positively associated with the commercial success of licenses (Hypothesis 1), and as LME increases, upfront fixed-fee payments decrease while royalty rates increase (Hypothesis 2), showing evidence of how LME use the contract payment structure to signal value to licensees. Furthermore, we find three contingencies that accentuate the positive LME-signaling relationship and lead to stronger signals: inventions heavily dependent on academic science (Hypothesis 3), greater inventor experience (Hypothesis 4), and wider patent scope (Hypothesis 5). The selection and matching mechanisms of LME argued for each contingency were generally validated through additional analyses. We discuss the implications of these findings in this section.

Implications for Signaling Theory Research

Our study offers several theoretical advancements to the signaling theory literature. We investigate how sellers can use contract payment structures to signal value to prospective buyers. We demonstrate the importance of evaluating signals in terms of a unified framework combining the seller's ability to signal value through the contract payment structure to buyers who need a signal to overcome doubts caused by information asymmetry. We establish how ability influences signal strength and its adjustability depending on the need for it. Given our emphasis on experience throughout the study, we also display how signaling ability can be a learned skill focused on identifying valuable opportunities and conveying these possibilities to prospective buyers. In the following section, we elaborate on each of these implications.

Signaling through the contract payment structure. The contract payment structure—the combination of upfront fixed and performance-based royalty payments—can be viewed as a form of pricing intellectual property. Pricing as a signal has actually received relatively little attention in the management literature, despite being at the heart of most signaling models in the economics literature. (See Appendix A for the literature review detailing the limited research.) We studied a setting where the predictions of economic theory could be verified by studying pricing decisions of the licensing managers. Our central claim has been that intermediaries (the licensing mangers in our context) signal value to skeptical buyers by trading guaranteed upfront payment for deferred royalties. Intermediaries are only willing to propose such arrangements if they determine that the value generated from the royalties of the intellectual property will exceed the forgone upfront payments. Otherwise, standard bargaining principles are more effective: using the contract structure to settle clashing interests by capturing as much return as possible in guaranteed and royalty payments. Our analysis confirmed our central claim about signaling through contract payment structures and the importance of sender and recipient characteristics for signal strength.

Our work offers additional insights regarding how signals operate for those affiliated with highly capable or high-status partners. From the prior research, we know that well-connected entrepreneurs and start-ups are more likely to receive investments from venture capitalists (Hsu, 2007; Shane & Cable, 2002), and those with strong and reputable partners are more likely to have higher valuations (Stuart, Hoang, & Hybels, 1999). When a licensing manager's experience is taken into account, we observe that the contracts are structured to signal the potential value of working with highly experienced inventors through a combination of an even lower fixed-fee and higher royalty rates (see Table 3, Model 1). From these results, we argue that even in situations that involve highly capable inventors, the licensing manager's experience still offers opportunities to employ signals to convey potential value, in contrast to a more common bargaining explanation.

Credible and effective signals depend on both ability and need. We advance signaling theory by our emphasis on the ability and need to signal, which allows us to comment on the nature of a good signal: one based on the sender's ability that fulfills the need to address information asymmetry. First, the signal purposefully links the sender's ability to his or her profits, allowing the sender to vary the signal strength intentionally and specifically to their intended receivers. This is not trivial, as a large portion of the signaling literature has studied signals that are unintended by-products of a signal sender's actions, such as getting an education or embedding a firm in a network. Education is not undertaken with the primary aim of signaling, and thus is a noisy measure of ability (Sauer et al., 2010). Similarly, networks formed by young firms are path-dependent and choice-constrained (Stuart, 2000), and are thus a noisy measure of future firm profitability. In our context, the signal is closely aligned with the signal sender's ability. This increases the signal's accuracy and eases the recipient's interpretation.

Second, a good signal fulfills a need, namely to communicate an uncertain value to the signal recipient. Many signals studied in the literature cannot be targeted uniquely at one recipient, and the signal sender may then face complicated trade-offs, as different audiences interpret signals differently (Gomulya & Boeker, 2014). We are fortunate that our context uses a signal that is specific to each licensee, as the contract terms are uniquely established in each negotiation.

Up to now, the empirical findings of signaling theory on contract structure have been mixed, with some research finding support for signaling (Macho-Stadler et al., 2008; Shane et al., 2006), while others do not (Hegde, 2014; Lafontaine, 1993). To help tackle the inconsistent empirical results of the theoretical signaling models, we developed a comprehensive framework that expanded the scope of inquiry to cover the sender's entire signaling environment to improve assessments of signal strength (Connelly et al., 2011). We derived our own theoretical model that looks at the characteristics of the sender and the environment to predict signaling ability and need, and thus ultimately the strength and fit of the signal. Signaling ability and need are a joint prerequisite for sending a signal, yet the literature does not question how or why they arise (assuming that both are present and mostly fixed). We argue that the inconsistent results could be resolved, in part, by better integration of these two features.

Adjusting signal strength based on ability and need. We developed predictions on some of the contingencies that were speculated by Connelly et al. (2011) to change the strength of, and the need for, a signal. Examining these contingencies (our moderators) allowed us to demonstrate why predictions of signaling theory may be difficult to confirm in prior work that did not consider changes in the signaling environment (Heil & Robertson, 1991; John & Williams, 1985; Ndofor & Levitas, 2004). Depending on the contingencies, the relationship between licensing-manager-experience and contract-payment-structure outcomes either strengthened or weakened with changes in the need to signal. Our results provide new empirical support that confirms how signals address information asymmetry obstacles that normally lead to unproductive negotiations. Thus, we expand our understanding of how signals operate in environments where the signal sender's ability and need to signal vary. This stands in contrast to the static environment typically assumed in this literature.

Moving from innate signaling ability to gained experience. Up to now, signaling research has assumed a sender's innate ability to make a fairly accurate assessment of their environment and to signal accordingly (e.g., signaling through education—Morris, Alvarez, Barney, & Molloy, 2016; Trevor, 2001). Similarly, a firm who wants to convey information about its organizational, environmental, product or process quality (e.g., Jayasinghe, 2016; King, Lenox, & Terlaak, 2005; Montiel, Husted, & Christmann, 2012; Ramchander et al., 2012) is naturally expected to know whether they excel in that dimension or not before attempting to signal. Our work revisited the fundamental assumptions about whether and how the signal sender acquires superior information to communicate to the receiver. We argued that experienced licensing managers can better discern an invention's market value by exercising their skill in selecting the most promising inventions and matching them with capable licensing partners for commercialization. This simultaneously increases the quality of the invention and lowers the information asymmetry presented to risk-averse licensees.

Implications for Academic Entrepreneurship Research

In the academic entrepreneurship literature, researchers investigate how academic inventions are commercialized amid the uncertainties inherent in emergent technologies. In one research stream, scholars focus on how the experience and knowledge gained from past endeavors contribute to evaluating and pursuing new business opportunities based on their inventions (Gruber, MacMillan, & Thompson, 2008; Shane, 2000). In another research stream, the emphasis has been on how intellectual property rights (Thursby & Thursby, 2003) or the design of contract structures (Jensen & Thursby, 2001) influence commercial outcomes. Our research bridges both streams by its focus on a specific type of experience—the ability of licensing managers to select promising inventions, to match them with capable licensing firms, and to construct a credible signal using the contract payment structure to bring parties together in an agreement. By linking the opportunity-evaluation and licensing-contract-design streams, our study yields deeper insights into how and why some inventions advance to commercialization in ways that prior research from either stream has not.

At the heart of entrepreneurship is the pursuit of value-creating opportunities and the mobilization of sufficient resources to successfully undertake them despite uncertain conditions (Aldrich & Ruef, 2006; McMullen & Shepherd, 2006; Stevenson & Jarillo, 1990). In our context, we highlight how licensing manager experience improves the selection of promising opportunities (from the pool of new inventions disclosed to the TTO) and the matching of these opportunities to the commercialization partners best prepared to generate a financial return. Despite the lack of complete information about a technology's efficacy and a partner's capabilities, experienced licensing managers gain the skills to construct contract terms that generate greater value for all parties involved. As the licensing managers in our context gain experience, they become better at identifying quality inventions and matching them with the appropriate licensee—increasing value while reducing the risks of commercialization. To accomplish this, they signal a willingness to give up a sure upfront payment in exchange for higher, but uncertain, returns. Experience also brings licensing managers a greater appreciation of possible contingencies, such as differences in the maturity of the technology, and the expertise and relationship history of the licensing partner. This deeper awareness allows them to adjust contract terms based on changes in uncertainty due to lower information asymmetry. Generalized more broadly, our study opens up new conceptual pathways for understanding how specific domain experience leads to improvements in opportunity selection and matching these opportunities with the appropriate resources—such as recruiting co-founders, engaging with supply-chain partners, or forming alliances—despite the uncertainties caused by incomplete information (Grégoire & Shepherd, 2012). Such skills lead to the development of contingent agreement structures that bind parties together through shared value creation. The empirical evidence indicates that repeat and portfolio entrepreneurs are more likely to identify better opportunities (Baron & Ensley, 2006) to structure deals differently (Hsu, 2004) and to achieve better outcomes (Stuart & Abetti, 1990). Our work expands this knowledge base about how experience translates into pursuing value-creating opportunities through academic–industry collaborations aimed at commercializing science.

Implications for Collaborative Agreements Research

Our study also broadens our understanding of how collaborative agreements between organizational actors are created, and highlights the vital role that intermediaries (the TTOs in our context) play in this process. In contrast to brokers who simply bring together parties in a short-term transactional manner, intermediaries succeed by creating new value that incorporates the interests of all parties (Ashenfelter & Dahl, 2012). To accomplish this, intermediaries embed themselves into the agreements and only benefit if the performance of the collaboration succeeds in the long run (March & Olsen, 1989). Rather than employ conventional bargaining tactics to secure the largest returns only for themselves, our research demonstrates how collaborative agreements can actually produce benefits for all parties. Although the conceptual arguments for this alternative viewpoint have already been published, our study demonstrates and tests the mechanisms by which intermediaries form such agreements in ways that no prior field research has shown.

We report how integrative agreements are designed by experienced intermediaries who are "givers" to their collaborative partners (giving up sure upfront payments for an increased share of risky performance payments which all parties benefit from) rather than simply intermediaries who are "takers" (demanding higher fixed and performance payment) from negotiations (Grant, 2013). In our context, the early-stage status of these inventions makes information asymmetry a significant obstacle to overcome in order for a fruitful collaboration to occur. The prospects of reaching a stalemate remain high, but in our framework, experienced intermediaries can forge agreements by signaling potential value-creation opportunities through contract terms. To the best of our knowledge, our study is the first to apply signaling principles to explain how and why experienced intermediaries determine the ideal contract structures for demonstrating the value of early-stage inventions.

Our insight into the construction of integrative agreements also advances new thinking about the specific attributes of how these agreements come together. Ours is one of the first field studies to show how a licensing manager's experience influences the construction of collaborative agreements. Although prior experimental studies have established the importance of understanding the role of experience in mediation (Bazerman & Neale, 1985; Bazerman, Neale, Valley, Zajac, & Kim, 1992), our findings actually pinpoint its influence, both in terms of the direct relationship on commercial success as well as the contingent influences of the inventor and invention's characteristics.

Managerial Implications

Our study insights have immediate applications for practitioners who need to bring together parties who are separated by information asymmetry and risk aversion. One of the biggest obstacles in forging effective licensing deals is the inability for partners to come to an agreement. The attitudes of optimistic inventors and the risk-averse preferences of the licensing partners can easily lead to market failure: both parties disagree about their relative and total contributions to value creation, especially when there are significant technological uncertainties (Dushnitsky, 2010). Our research provides practitioners a framework for resolving this stalemate. The licensing managers in our context were guided by their experience, which allows them to be more selective about the best inventions to bring to market, and the best firms with which to collaborate. Experienced managers signal this additional value through contract structures. Similar to ways in which managers benefit by issue-framing in contract development (Neale & Bazerman, 1985; Weber & Mayer, 2011, 2014; Weber, Mayer, & Macher, 2011), experienced intermediaries can apply their insights from prior contracts to signal, match, and shift contract terms in ways that motivate parties to come together and expend the effort required to achieve the best outcomes. Thus, one direct implication is that organizations involved in technology licensing should cultivate practices for inexperienced licensing managers to learn from their more-experienced counterparts. This can occur through direct mentoring or pairing senior and junior licensing managers together to conduct deals to increase the rate of learning and knowledge sharing (March, Sproull, & Tamuz, 1991; Toft-Kehler, Wennberg, & Kim, 2014). Given the counterintuitive nature of credible signals, direct and repeated experience offers licensing managers opportunities to improve their abilities to construct winning agreements. Having more opportunities to select inventions, match them with firms, and send credible signals in the contract payment structure also allows licensing managers to realize that no two contracts need to look alike. Experience permits them to adjust their signals to the corresponding circumstances and respond to varying levels of uncertainty caused by information asymmetry.

To appreciate the scope of these implications, it is helpful to understand the size and growth prospects for our context. According to recent statistics, firms are licensing technologies from universities at an increasing rate, with more than 5,000 licenses (with year-over-year growth of 4.7%) and a total licensing university income of $2.6 billion (with year-over-year growth of 6.8%) in 2012 as reported by the Association of University Technology Managers

(AUTM, 2015). When intra-firm licensing is added, patent revenue in the U.S. reached $45 billion in 2013 (BEA, 2014).

Limitations and Avenues for Future Research

Although we exercised care in designing our study, it is not without limitations. We briefly describe how future research may yield additional insights beyond those we have offered here. There are two avenues to improve our theory to predict contract payment structure design. First, while we isolated both the selection and matching mechanisms in the post-hoc analysis, future work should build on our findings to verify the relative magnitude of these mechanisms. Second, new research should seek to determine the initial reference points of parties who enter into a negotiation and assess how these reference points influence contract structure. This includes investigating licensing manager experience in terms of differences between contract experience and prior interactions with multiple inventors more carefully. Future studies should investigate other contexts in which collaborative agreements are constructed to build upon our study's findings. While our research site offers a host of advantages to observe and isolate inventions and licensing capabilities that may not be as evident in other contexts, we speculate that in most large organizations that license technology, the theoretical principles from our framework will generally apply. Future work should assemble licensing data from multiple TTOs as well as non-academic corporate licensors to better understand the increasing economic importance of licensing-in and licensing-out inventions. Moreover, the conceptual framework employed in our study can also be applied to other settings where intermediaries assist buyers and sellers who do not easily agree on quality and value, such as artistic and cultural products, and professional athletics.

CONCLUSION

Every year, billions of dollars are invested in basic science. However, many promising inventions are overlooked because of the difficulties associated with assessing commercial opportunities. In situations that involve technological uncertainties and require collaboration between multiple parties, experience plays a vital role in producing value-sharing agreements. Our study shows how experienced licensing managers create value-sharing arrangements in ways that benefit society through the commercialization of breakthrough science. Experienced intermediaries maximize the value produced from an uncertain undertaking by improving the selection of promising projects and matching them with capable partners to form a fruitful collaboration. We advance signaling theory by developing a comprehensive framework that integrates the ability and needs of the signaler, and the intentionality and specificity of the signal. By signaling high potential value outcomes through a combination of upfront fixed-fee and delayed royalty rates, the experienced licensing managers in our context engender confidence in otherwise reluctant parties and pave the way toward value-generating outcomes.

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APPENDIX A

In Appendix A, we present a summary table classifying the signaling literature in the management field according to the type of signal used and the properties of the signal along four dimensions: whether the signal can be modified with changing *ability* and *need* of the signal sender and whether the signal is *intentional* or not as well as whether it is *specific* to the signal recipient or broadcast for multiple recipients. These dimensions were chosen because a signal that scores highly on all these dimensions is more likely to be a true and unbiased signal, as it is reactive to the signaling environment and uniquely crafted for the focal interaction.

By and large, the literature exploring signaling has assumed that there is a constant ability and limited variability in the need to signal, and then explored what types of signals are being sent; what makes signals more or less effective; or how multiple signals interact. The table reveals very few studies that extensively address all four dimensions. As a result, we still lack a comprehensive understanding about untangling the underlying reasons to send out signals or not.

By studying bilateral contracts written by a signal sender with time-varying ability, we have a setting that displays all four desirable dimensions of a signal. It is also a setting that enables us to study the antecedents of the signaling decision. We base our arguments on the literature whenever we refer to the interactions between the dimensions that have already been studied in the literature, and use our theoretical model to establish the framework when considering all four dimensions simultaneously.

TABLE A1
Signaling Literature Overview

Context	Ability	Need	Intentional	Specific	Comments
Bilateral contracts	Y	Y	Y	Y	Bilateral contracts specifying a trade-off between payment types can be crafted to send a signal exclusively tailored to the exchange partner. Payment terms are a particularly strong signal as they have an immediate impact on the revenue of the signal sender that is largely independent of external factors. However, very little research has been published integrating all four aspects.
Education			Y	Y	Education is generally assumed not to affect ability (Spence, 1973). Individuals have limited flexibility to tailor the costly signal to different needs (Merluzzi & Phillips, 2016; Sauer et al., 2010). The revenue impact of the signal is moderated by labor market characteristics (Merluzzi & Phillips, 2016; Trevor, 2001).
Certification	Y	Y	Sometimes		Certification serves more than one purpose (Hsu & Ziedonis, 2013) and the outcome is observed by all stakeholders. The signal sender may have some discretion about certification options to pursue (Jayasinghe, 2016; Montiel et al., 2012; Okhmatovskiy & David, 2012). The signal's value can be affected by external factors such as corruption (Montiel et al., 2012) or the signaling behavior of competitors (Ramchander et al., 2012).
Announcement	Sometimes	Y	Y		Announcements are broadcast to multiple receivers (Stern & James, 2015). While announcements can be flexibly tailored to the need (Sanders & Carpenter, 2003) and sometimes the ability (Okhmatovskiy & David, 2012), they risk being perceived as lacking in substance (Gomulya & Mishina, 2017). The impact of the signal depends on the sender's perception of the receivers (Gomulya & Mishina, 2017; Stern & James, 2015).
Network	Y				Networks serve more than one purpose, e.g., financing (Higgins & Gulati, 2006) or knowledge sharing (Reagans et al., 2015; Stuart, 2000; Reuer & Koza, 2000; Soh et al., 2004). The signaling function of the network is frequently incidental in nature. Hence, Kilduff et al. (2016) warn against seeing a signal where there may be none, and show that returns are not always forthcoming. The variety of purposes of network formation also means that the value of the signal varies with the exchange partner (Reuer & Ragozzino, 2012).
Reputation	Y				Reputation and status are path-dependent and evolve with the actor's ability (Pollock et al., 2015; Lee, 2010). This limits the sender's ability to manipulate it as a signal. Reputation is a relative construct as it exists in comparison to other actors (Lee, 2010; Huang & Washington, 2015). Thus the benefits from reputation as a signal can be greatly affected by the environment (Kovács & Sharkey, 2014).
Pricing	Y	Y	Sometimes	Sometimes	Extensive theoretical work shows that pricing structure can be used for signaling (Milgrom & Roberts, 1986; Bagwell & Riordan, 1991). Kirmani and Rao (2000) claim that empirical evidence of price as a signal of quality is equivocal. Etzion and Pe'er (2014) argue that the mixed empirical results are due to the use of cross-sectional data rather than longitudinal data, as the environment and the sender change.

Notes: This summary table is based on a review of over 110 articles on signaling from four management journals (*ASQ*, *AMJ*, *Org Sci*, *SMJ*) from 2000 to 2016.

APPENDIX B

Signaling Model Derivation

A risk-averse licensing manager with utility function $U(x)$ licenses an invention that can take on two values, V_L and V_H, depending on the quality of the match between the invention and the licensee. The licensing manager finds a good (poor) match with probability q $(1-q)$. The expected value of the invention is $W = qV_H + (1-q)V_L$. After contracting, the licensing manager receives a share $1-\phi \in [0,1]$ of the expected value W (the remaining ϕ go to the licensee).[7]

The contract contains two different terms: an upfront payment F and a royalty rate r that is calculated on the value of the invention. Note that in the absence of information asymmetry, when a risk-averse licensing manager signs with a risk-neutral licensee,[8] the optimal contract contains an upfront payment only.

As the licensing manager gains experience, she chooses more valuable inventions to propose to the licensee—i.e., V_L and V_H increase—and is more likely to achieve better matches—i.e., q increases. The licensing manager's experience, however, is private information and not observable to the licensee.

For simplicity's sake, assume that there are only two levels of licensing manager experience (LME): no experience (subscript *NE*) or a fixed level of experience (subscript *E*).[9] We have $V_{E,H} \geq V_{NE,H}$, $V_{E,L} \geq V_{NE,L}$ and $q_E \geq q_{NE}$. This means that $W_E \geq W_{NE}$. The values for V_H, V_L, and q are known to the licensee, but the licensee does not know the LME.

For a given no-experience contract (F_{NE}, r_{NE}), the experienced licensing manager can signal her experience and maximize her utility if she solves the following:

$$\max_{F_E, r_E} \Omega = q_E U(F_E + r_E V_{E,H}) + (1-q_E) U(F_E + r_E V_{E,L})$$

subject to

$$q_{NE} U(F_{NE} + r_{NE} V_{NE,H}) + (1-q_{NE}) U(F_{NE} + r_{NE} V_{NE,L})$$
$$\geq q_{NE} U(F_E + r_E V_{NE,H}) + (1-q_{NE}) U(F_E + r_E V_{NE,L})$$

$$(1-r_E)(q_E V_{E,H} + (1-q_E) V_{E,L}) - F_E \geq \phi(q_E V_{E,H} + (1-q_E) V_{E,L})$$

The first constraint is the licensing manager's incentive compatibility constraint, i.e., the inexperienced licensing manager receives a higher utility from choosing the contract that corresponds to her type than by choosing the contract that is designed by the experienced licensing manager. This ensures a separating equilibrium with the truthful revelation of the LME. The second constraint is the licensee's individual rationality constraint, and it ensures that she earns at least a fraction ϕ of the total value created.

The inexperienced licensing manager does not signal, and optimally chooses $r^*_{NE} = 0$ and $F^*_{NE} = (1-\phi)(q_{NE} V_{NE,H} + (1-q_{NE}) V_{NE,L})$. We substitute into the experienced licensing manager's problem to obtain:

$$\max_{F_E, r_E} \Omega = q_E U(F_E + r_E V_{E,H}) + (1-q_E) U(F_E + r_E V_{E,L})$$

subject to

$$U(F^*_{NE}) \geq q_{NE} U(F_E + r_E V_{NE,H}) + (1-q_{NE})$$
$$U(F_E + r_E V_{NE,L}) F_E \leq (1-\phi-r_E)(q_E V_{E,H} + (1-q_E) V_{E,L})$$

Both constraints set an upper limit on F_E for a given r_E; thus, only one holds with equality, and the other one is redundant. We use the binding constraint to substitute F_E out and optimize over r_E only. We prove that the royalty rate will be non-zero for the experienced licensing manager.

Define a new variable $\tilde{x} = x - F_E$ and the function $\tilde{U}(\tilde{x}) = U(x) - U(F_E)$. This function is concave in $\tilde{x}$. Then we can rewrite the optimization problem as follows (assuming the first constraint is binding, and the second is redundant—the reverse assumption can be worked out similarly):

$$\max_{F_E, r_E} \Omega = U(F_E) + q_E \tilde{U}(r_E V_{E,H}) + (1-q_E) \tilde{U}(r_E V_{E,L})$$

subject to

$$U(F^*_{NE}) = U(F_E) + q_{NE} \tilde{U}(r_E V_{NE,H}) + (1-q_{NE}) \tilde{U}(r_E V_{NE,L})$$

Or:

$$\max_{r_E} \Omega = U(F^*_{NE}) - (q_{NE} \tilde{U}(r_E V_{NE,H}) + (1-q_{NE}) \tilde{U}(r_E V_{NE,L})) + q_E \tilde{U}(r_E V_{E,H}) + (1-q_E) \tilde{U}(r_E V_{E,L})$$

We take the first order derivative of the objective over r_E at $r_E = 0$ and find that it is positive, thus indicating that the experienced licensing manager should optimally set a non-zero royalty rate $r^*_E > 0 = r^*_{NE}$:

$$\Omega'(r_E = 0) = -(q_{NE} V_{NE,H} \tilde{U}'(0) + (1-q_{NE}) V_{NE,L} \tilde{U}'(0)) + q_E V_{E,H} \tilde{U}'(0) + (1-q_E) V_{E,L} \tilde{U}'(0)$$

$$\leftrightarrow \Omega'(r_E = 0) = \tilde{U}'(0)(q_E V_{E,H} + (1-q_E) V_{E,L} - (q_{NE} V_{NE,H} + (1-q_{NE}) V_{NE,L}))$$

$\leftrightarrow \Omega'(r_E = 0) = \tilde{U}'(0)(W_E - W_{NE}) > 0$ It further follows that

$$F^*_E < F^*_{NE}, \text{because}$$

$$U(F_E) = U(F^*_{NE}) - q_{NE} \tilde{U}(r_E V_{NE,H}) - (1-q_{NE}) \tilde{U}(r_E V_{NE,L}).$$

Thus we find that the main effect of LME causes an increase in the royalty rate $(r^*_E > r^*_{NE})$ and a decrease in the upfront payment $(F^*_E < F^*_{NE})$.

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[7] This representation of the bargaining game is typical of the Nash bargaining equilibrium model. The relative bargaining power of both parties will affect the share that each party receives.

[8] Or at least with a licensee who is less risk-averse than the licensing manager.

[9] The results can be extended to an arbitrary number of experience levels or even to continuous experience levels.

Numerical Examples

TABLE B1
Model Parameters

Notation	Description
$u(x) = \sqrt{x}$	Licensing manager's utility function
$\phi = 80\%$	Nash bargaining parameter
$V_{0,L} = 1; V_{1,H} = 2; q_0 = 0.5$	Values for licensing manager without experience
$V_{1,L} = 1.05; V_{2,H} = 2.05; q_1 = 0.6$	Values for licensing manager with low experience
$V_{2,L} = 1.1; V_{2,H} = 2.1; q_2 = 0.7$	Values for licensing manager with high experience

FIGURE B1
Contrast Between High and Low Experienced Licensing Manager's Payment Terms

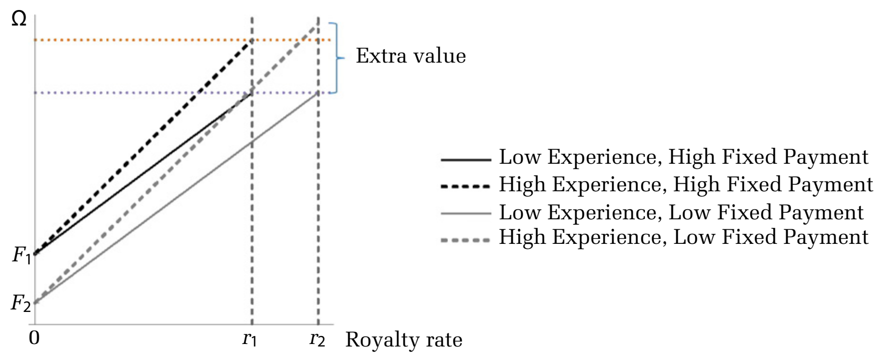

TABLE B2
Hypothesis 2. Licensing Manager Experience

Experience	Upfront payment	Royalty rate (%)
Low	0.07	15.55
High	0.02	19.07
	Decrease: −0.05	Increase: +3.52

Hypothesis 3. Science-Intensive Inventions

Base case without experience shows higher variability in values and lower matching probability. We argue that for science-intensive inventions, the selection and matching mechanisms of experienced licensing managers are more impactful, leading to (relatively) larger increases.

TABLE B3
Parameter Values

Parameter	Description
$V_{0,L} = 0.5; V_{1,H} = 2.5; q_0 = 0.4$	Values for licensing manager without experience
$V_{1,L} = 0.6; V_{2,H} = 2.6; q_1 = 0.5$	Values for licensing manager with low experience
$V_{2,L} = 0.7; V_{2,H} = 2.7; q_2 = 0.6$	Values for licensing manager with high experience

Compared to the base case (Hypothesis 2), the upfront payment decreases and the royalty rate increases at a greater rate when inventions are science-intensive.

TABLE B4
Contract Terms

Experience	Upfront payment	Royalty rate (%)
Low	0.12	12.41
High	0.05	17.20
	Decrease: −0.07	Increase: +4.79

Hypothesis 4. Inventor Experience

Base case without experience shows higher variability in values and identical matching probability. We argue that for inventors with experience, the selection mechanism is more impactful and leads to a higher value improvement, whereas the matching mechanism is unaffected.

TABLE B5
Parameter Values

Parameter	Description
$V_{0,L} = 0.5$; $V_{1,H} = 2.5$; $q_0 = 0.5$	Values for licensing manager without experience
$V_{1,L} = 0.6$; $V_{2,H} = 2.6$; $q_1 = 0.6$	Values for licensing manager with low experience
$V_{2,L} = 0.7$; $V_{2,H} = 2.7$; $q_2 = 0.7$	Values for licensing manager with high experience

Compared to the base case (Hypothesis 2), the upfront payment decreases and the royalty rate increases at a greater rate when the inventor has experience.

TABLE B6
Contract Terms

Experience	Upfront payment	Royalty rate (%)
Low	0.14	12.22
High	0.06	17.21
	Decrease: −0.08	Increase: +4.98

Hypothesis 5. Patent Scope

Base case without experience shows identical value improvement and matching probability. We argue that inventions with a wide patent scope are more difficult to match and reduce the impact of licensing manager experience, whereas the impact of experience on the selection mechanism is unaffected.

TABLE B7
Parameter Values

Parameter	Description
$V_{0,L} = 1$; $V_{1,H} = 2$; $q_0 = 0.5$	Values for licensing manager without experience
$V_{1,L} = 1.05$; $V_{2,H} = 2.05$; $q_1 = 0.55$	Values for licensing manager with low experience
$V_{2,L} = 1.1$; $V_{2,H} = 2.1$; $q_2 = 0.6$	Values for licensing manager with high experience

Compared to the base case (Hypothesis 2), the upfront payment decreases and the royalty rate increases at a greater rate when the invention has a wider patent scope.

TABLE B8
Contract Terms

Experience	Upfront payment	Royalty rate (%)
Low	0.10	14.00
High	0.03	18.25
	Decrease: −0.07	Increase: +4.25