Intellectual Property Contracts: Theory and Evidence from Screenplay Sales

by

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ABSTRACT

This paper presents a model of contracts for the sale of intellectual property. We explain why many intellectual property contracts are contingent on eventual production or success, even without moral hazard on the part of risk-averse sellers. Our explanation is based on differences of opinion between buyers and sellers with regard to the seller's competence. Unlike signaling models, our framework is founded on learning by buyers and sellers and on the sellers' reputation building. Thus, we are able to derive predictions regarding the impact of the seller's experience on the nature of the contract. In particular, our model predicts that more experienced sellers will be offered a different mix of cash and contingency payments than inexperienced sellers. We also discuss the probability of sales as a function of seller and product characteristics. Some predictions of the theoretical models are supported by an analysis of screenplay sales data.

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1. Introduction

Every new product or service starts with an idea. This idea, in the form of a patent, an architect's design, a sketch of a new product or a screenplay is sold to a commercial entity that produces the product and brings it to market. We refer to the idea for a new product (an intermediate creative good), in whatever form, as intellectual property (IP). Examples, in addition to those just mentioned, abound. A small biotech company may sell a compound to a pharmaceutical giant that can develop it into a useful drug. A new design may be sold to a company who may or may not be able to turn it into a useful product. In the movie industry, deals of the type we have in mind are most common; for example, writers sell screenplays or novels to movie studios. This paper provides a multi-period model for intellectual property contracts that is consistent with some of the stylized facts regarding these contracts. In particular, we derive implications for equilibrium IP contracts as a function of the seller's experience. We also test some implications of the model on a screenplay data set.

Intermediate creative goods are often sold on a contingency basis, i.e., part of the seller's compensation depends on the eventual production or success of the property. This is evident in many book contracts, patent contracts, and other IP sales agreements. In our screenplay dataset, for example, 62% of the contracts are contingent upon production. In IP transactions, generally the seller (an individual or a small family-owned business) is likely to be risk averse, and the buyer (typically a large corporation) is likely to be approximately risk neutral with respect to any given contract. In such situations, standard agency theory explains contingencies as a response to moral hazard. That is, the risk-averse agent optimally bears some risk in order to provide her with incentives to perform. Sales of these types of intellectual property, however, rarely involve moral hazard on the part of the seller. Once a patent or a screenplay is sold, generally no further significant effort on the part of the seller is required, so moral hazard does not seem to be an appropriate explanation of contingencies in our context.

Some signaling models can also produce contingent contracts. However, there are important differences between our set up and a signaling set-up. First, in signaling models you have to assume that one side is better informed than the other. Indeed, two papers discussing an identical problem in the IP space start with opposite assumptions- Galini and Wright (1990) assume that the licensor (seller) has private information, whereas Beggs (1992) assumes that the licensee has better information. Furthermore, signaling models by their very nature strive to achieve a separating equilibrium by the choice of contracts revealing the type of property or the type of seller as the deal is struck. Our set up suggests that both sides to the transaction may be uninformed. One side may be more optimistic than the other but both sides learn together as additional transactions take place. Thus we have implications for the type of contracts offered to people at different stages of their career, which a signaling model cannot produce. Both types of models can yield contingent contracts; however, we believe our reputation building approach may be more suitable for real life IP contracts.

More precisely, our model starts with differences of opinion between buyer and seller as to the seller's competence to produce a viable property. In particular, we assume competence is not directly observable by either party, and that the seller is more optimistic about her competence than the buyer. As is well known, such differences of opinion provide a reason for the parties to "bet" with each other on observable outcomes that are correlated with the issue about which the parties disagree, even if one or both parties is risk averse. In our case, these bets take the form of contractual payments to the seller, which are contingent on either production or on successful outcomes in production. Since we assume that

the seller is risk averse, while the buyer is risk neutral, not all contracts are contingent. In particular, the difference of opinion must be large enough to overcome the seller's risk aversion for the optimal contract to include contingencies.¹

In addition to the focus on differences of opinion, our model features repeated transactions between sellers and buyers. We believe this is a novel feature in the IP contracting literature. It has the interesting implication that more experienced sellers are more likely to receive non-contingent contracts. This follows because, as a seller becomes more experienced, more information is available to the parties, and the additional information narrows the differences of opinion. Also, we can show that as the seller reputation improves, he is more likely to receive a cash contract.

It is difficult to test such implications, because of the lack detailed data on IP contracts. Even our screenplay database provides information only on some features of the contracts. However, we are able to test our result that more experienced sellers are more likely to have non-contingent contracts as well as one or two other implications of the model. We find that the empirical implications that can be tested on this data are consistent with the model.

Before proceeding to the model description, we relate this paper to the relevant contracting literature.

2. Literature Review

This paper is related to an enormous literature in contracting and borrows ideas from several types of papers. The disagreement literature dates back to Leland and Pyle (1977)². However, there and in other signaling papers, it is assumed that one side, usually an insider, knows the true "quality" of the product that is being sold. This is also the prevailing view on intellectual property contracts. Gallini and Wright (1990) assume that the licensor (the inventor) has private information regarding the value of the invention, and under several conditions, they find that the optimal contracts call for an "output based" (contingent) payment (proposition 1, ibid. p. 151) that will be taken by the high types and avoided by the low types, creating a separating equilibrium. However, Beggs ((1992) says that "the licensee (buyer) may have a better idea of value than the owner. This is especially plausible if one thinks of the buyers as a large company which will have a very clear idea of the market and the seller as a small inventor who may have a very hazy idea of such things" (ibid. p. 172). Of course, under these circumstances the optimal contracts are different than the ones envisioned by Gallini and Wright (1990) in a very similar set up (binomial value distribution). Beggs (1992) analyzes quite a few cases depending on who makes the offer and the equilibrium refinement used.

In contrast, our paper does not take a stand about the information structure; it only considers optimism and pessimism. As far back as Lovell (1968) quoted in Gallini and Wright (1990, p. 148) "a common complaint" among manufacturers was that "there is a tendency for the licensor to be overly optimistic about the commercial significance of the licensed innovation". Landier and Thesmar (2009) document entrepreneur optimism empirically. There are some recent papers that consider the impact of different assessments and beliefs on pay and capital structure decisions, and some of the ideas are similar,

¹ There are, of course, alternative explanations for the contingencies we observe. It may be that the seller is less risk averse than the buyer, but this seems unlikely in our context. Alternatively, one can conceive of an adverse selection or a signaling model. Our model, however, provides a simpler framework that closely resembles the institutional set up in practice.

² There are fewer papers that consider "pure" disagreement outcomes (with less precisely specified information structure), for example, Samuelson (1992) or Brunnermeier et al. (2014).

but there are important differences. In particular, moral hazard plays a key role in these papers but not in ours, and reputation effects are important in our work but not in these studies (see Adrian and Westerfield (2009) and Landier and Thesmar (2009)).

Our model also differs from much of the reputation/career concerns literature (e.g. Jensen and Murphy (1990), Gibbons and Murphy (1992)) where the purpose of the contract is to induce optimal effort. Thus, for example, in such models, stronger incentives are required towards the end of someone's career, since a given level of performance sensitivity will have much less of an impact when the remaining career is short. Our model is more in line with ability revelation models (on these distinctions see for example, Greenwald (1986), Gibbons and Katz (1992), Topel and Ward (1992), Von Wachter and Bender (2006) or Waldman (1984)) but again, we feature no effort component and uncertainty on both sides.

We cannot do justice to the IP literature. However, we can briefly mention that much of the literature on IP is concerned with legal aspects of contracting or protection of IP rights. (See for example, Varian (2000, 2005), Schankerman and Scotchmer (2001), or Havide and Kristiansen (2012).) Some papers consider the impact of contracting on innovation, for example, Shavell and Van Ipersele (2001).

Other work has been done on licensing contracts, with a different focus from ours, for example, Kulatilaka and Lin (2006).

One of the reasons that IP contracts have not attracted much academic attention is the lack of adequate data. There are very few details on contracts for architectural designs or books (see Chevalier and Mayzlin (2006)) or in fact on most other contracts. There has been work on patents and biotechnology contracts (See for example Lerner (1995) and Lerner and Merges (1998)).³ Movie industry contracts have also not been generally available (Chisholm (1997) discusses a small sample of star contracts). Some work has been done on movie exhibition contracts (See Filson et al, 2007). Gil and Lafontaine (2012) suggest both theoretically and empirically that sharing contracts in exhibition may be a manifestation of flexible pricing rather than risk sharing or moral hazard. In that paper, the contracts are between two companies rather than an individual and a large corporation but there are some similarities in the modeling choices.

Finally, there are three recent papers that consider various aspects of the screenplay market. Goetzmann, et al. (2013) uses the same data set as we do to consider the role of soft information in pricing screenplays and whether screenplay prices may predict the success of resulting projects. Eliashberg, et al. (2007) also tries to predict the success of film projects using a textual analysis of screenplay "spoilers," i.e., detailed ex-post descriptions. The third recent paper, Luo (2014), provides a model and an empirical analysis of the decision to sell a completed screenplay vs. selling just a pitch.

The remainder of the paper is organized as follows. Section 3 describes the model. We present our comparative statics results in section 4 and our empirical tests in section 5. Section 6 concludes.

³ Venture capital (VC) contracts, for which there are good data, are similar to IP contracts in that entrepreneurs pitch ideas to venture capitalists. There is, however, an important difference from the case of IP. If the venture capitalist "buys" the idea (i.e., funds the resulting entity that brings the idea to market), the entrepreneur usually continues to provide services to the resulting entity. Consequently, there is a moral hazard issue that results in contracts that are complicated functions of the sequence of outcomes realized by the firm. As mentioned previously, suppliers of IP generally do not continue to be involved in producing the final product once their property has been sold. Consequently, many features of VC contracts, such as heavy dependence on final outcomes and exit provisions, are rarely observed in IP contracts (for empirical analyses, see for example Kaplan and Stromberg (2003), Lerner and Merges (1998), or Ravid and Bengtsson (2015); for theory, see Harris and Raviv (1989, 1995), or Ravid and Spiegel (1997)).

Appendices are in sections 7-10. Sections 7-9 present most of the formal results, while section 10 provides some additional institutional background.

3. Model

The model incorporates the features discussed earlier, in a simple, discrete framework. All notation is explained when introduced and also summarized in section 7.

Consider a seller (*S*, she) of a piece of intellectual property and a producer (*P*, he) who uses the property to produce a final product.⁴ *P* is risk-neutral, and both players live a finite number of periods, denoted by *T*, and discount future payoffs using a discount factor $\beta \in (0,1)$. *S* is risk averse in a special sense described below. Each period, *S* generates a piece of intellectual property that can be either "good" or "bad," but importantly, quality is not perfectly observable by either player. *S* can be either competent or incompetent. Competence does not change over time; however, the two players may have different probabilities that *S* is competent at any given period. We denote by q_t^i player *i*'s ($i \in \{P, S\}$) probability that *S* is competent as of the beginning of period *t*. We refer to q_t^P as *S*'s *reputation* at the beginning of period *t*. We assume that, initially, *S* is more optimistic than *P*, i.e., she believes she is competent with higher probability than does *P*. Formally, we assume $q_1^S > q_1^P$.

As noted, there is a large literature on over-confidence and excessive optimism that justifies this characterization (see for example, Hong and Kubik (2003), Malmendier and Tate (2005, 2009) or Graham et al. (2012)). Another rationale for over-optimism is the idea that, given other life choices, only ex-ante optimistic sellers will be present in the sample, as argued in Landier and Thesmar (2009). Unlike other disagreement papers (such as Landier and Thesmar, 2009 or Adrien and Westerfield, 2009), we assume that both agents are Bayesian and, therefore, respond to information in the same fashion.

Since we assume that both players have the same information, it follows that $q_t^S \ge q_t^P$, for all t^{5} . In general, we denote by $\Pr_i(E)$ the probability that player $i \in \{P, S\}$ assigns to the event *E*.

A competent S generates a good property each period with probability s > 0, while an incompetent S cannot generate a good property (probability 0).⁶ To distinguish the intellectual property input from the final product, we refer to the former as a "property" and the latter as an "output."

⁴ Having many identical producers would not change results as long as (i) producers do not disagree with each other regarding the initial reputation of the seller, (ii) the seller can negotiate with at most one producer for each property, and (iii) in each period, producers who do not negotiate with the seller in that period, can infer any information generated by the producer with whom the seller does negotiate in that period. (Later we argue that this is the case in our empirical setting.)

⁵We will also assume presently that, if *S* is competent, this is revealed if a property is successfully produced. In that event the two probabilities will both be one for all subsequent periods. Otherwise *S*'s probability that she is competent will continue to exceed *P*'s. The difference between seller and buyer may change over time however.

⁶ The assumption that an incompetent seller cannot produce a good property implies that once a seller produces a successful property, he is identified as a competent seller with certainty. All our results will go through if the probability that an incompetent seller produces a "good" property is positive as long as the probability that a competent player produces a "good" property is higher. The current assumption simplifies the analysis, allowing us to focus on the important features of the reputation-building process.

If *P* develops the seller's property into an output, we say that *P* "produces" the property. It costs the producer *e* to produce any property, good or bad. A good property, if produced, yields revenue *v*. We assume v > e. Both *v* and *e* are exogenous parameters. A bad property, if produced, yields zero revenue. We assume that the property is purchased as is, and the purchase ends the involvement of the seller in the production process. This is the case for example, with screenplays, where re-writes (if any) are generally commissioned from a different person under a different contract.

If *P* purchases a property, he may then perform an initial evaluation to ascertain whether the property is good or bad. This evaluation is assumed to be free (although adding a fixed cost will not change the results), and it results in a noisy signal $\tilde{R} \in \{g, b\}$ of the property's quality such that

$$\Pr(\tilde{R} = g | \text{good property}) = \Pr(\tilde{R} = b | \text{bad property}) = r \in \left(\frac{1}{2}, 1\right).$$

Thus, a good signal ($\tilde{R} = g$) is more likely than a bad signal ($\tilde{R} = b$) if the property is good, i.e., r > 1/2, and conversely, a bad signal is more likely if the property is bad. One can think in this context of r as the probability of receiving the "correct" signal, so r measures the quality of P's signal. The assumption that the accuracy of the signal is the same for both good and bad properties simplifies the exposition but doesn't affect the results.

The object of our analysis is to characterize the contracts between seller and buyer that will arise in the environment just described. In this context, a contract specifies an upfront cash payment, denoted *c*, and subsequent payments that are contingent on the outcome of the production (if any), denoted k_v if the production succeeds (and revenue is *v*) and k_0 if the production fails (and revenue is 0). This is a general formulation that accommodates cash contracts, contracts contingent on production and revenue sharing contracts. Note that a contract that offers a contingent amount that is paid if and only if the property is produced, but does not depend on revenue, is a special case in which $k_v = k_0$. This is the case in our screenplay data.

In general, one can imagine that any of the payments, c, k_v , and k_0 could be negative. That is, S may be willing to pay P to acquire the property (in order to generate the signal of its quality) or to produce an acquired property (again to generate information about the property and hence about the seller's competence). For example, academic journal submissions generally entail a payment by the author. In many markets, including the market for screenplays that we use to test some implications of the model, there are minimum cash payments dictated by a union, and contingency payments are constrained to be non-negative. Consequently, in much of the analysis we assume that $c \ge c_0 > 0$ and

 $K \equiv \left(k_{v}, k_{0}\right) \geq 0.^{7}$

⁷If we drop the constraints that the cash payment must exceed a minimum amount and the contingency payments must be non-negative, two outcomes that are ruled out by these constraints may become feasible, depending on parameter values. The first is that the seller is willing to pay the buyer to obtain the preliminary signal, even if there is no chance the buyer will actually produce the property. The second is that the seller is willing to pay the buyer to produce a property to generate the additional information provided by the success or failure of the project, even if the preliminary signal is bad. The first case can be ruled out with some relatively innocuous assumptions regarding the seller's outside opportunity. The model can easily accommodate negative payments at some cost in terms of the number of feasible cases. Results, however, would not be very different from those obtained below.

In order to model risk aversion in a simple fashion, we also assume that S "discounts" contingency payments relative to non-contingent payments. In particular, we assume that each \$1 contingency payment is worth only α to S, where $\alpha < 1$. This assumption leads to "bang-bang" contracts that involve choosing either the largest feasible contingency payment if q^S is sufficiently large relative to q^P or the smallest such payment otherwise. Modeling risk aversion in the usual fashion (as a concave von Neumann-Morgenstern utility function) would generally result in "interior" solutions. The behavior of these interior solutions in response to changes in the exogenous parameters would, however, be similar to that of our bang-bang solutions. Given the extra analytical burden of including concave utility functions, and the likelihood of similar comparative statics results, we have chosen this simpler modeling approach.

To summarize the model, we provide the timeline for each of our T periods:

- 1. *S* makes a pitch to *P*.
- 2. *P* and *S* negotiate a contract, (c, K).
- 3. If the property is sold, P pays c to S and
 - a. *P* receives the signal $\tilde{R} \in \{g, b\}$;
 - b. *P* decides whether to produce the property;
 - c. If *P* produces the property, the revenue (*v* or 0) is realized and publicly observed; *P* pays k_v or k_0 to *S*;
 - d. Both players update their probabilities that *S* is competent.
- 4. If the property is not sold, neither player updates his/her probability that S is competent.
- 5. The game moves to the next period.

3.1. Equilibrium Contracts

In this section, we describe the resulting equilibrium contracts. The discussion is informal and intuitive with the formal details relegated to the appendix (section 8).

Several additional assumptions will simplify the analysis by eliminating some uninteresting cases.

First, we assume that, in contract negotiations, the buyer has all the bargaining power. Formally, this implies that the present value of the seller's expected current and future payoffs resulting from any agreed-to contract is equal to the present value of her outside opportunity. We refer to the seller's outside opportunity as the "secondary market" (while the IP market is referred to as the "primary market") and also assume that, as the seller's reputation, q^P , improves, her per-period payoff in the secondary market, denoted $w(q^P)$, increases. Thus, an increase in the seller's reputation will result in a contract with greater value for her, if she receives a contract offer. This setup is analytically similar to assuming that the two players split the rents in some fixed proportion, while greatly simplifying the calculations. Formally, we make the following assumptions about $w(q^P)$.

Assumptions: $w' \ge 0$ with strict inequality for some values of q^p , w is weakly convex, and $w(0) \ge c_0$.

The first property just reflects the assumption, discussed above, that the seller's compensation in the secondary market is increasing in her reputation in the primary market. Convexity of w is used in

analyzing the comparative statics of the equilibrium outcomes. The assumption that $w(0) \ge c_0$ implies that $w(q) \ge c_0$ for all q, since w is increasing. This allows us to ignore some uninteresting cases.

Second, we assume that no information about the seller's competence in the primary market is generated by her activity in the secondary market.

Third, we assume that the producer cares only about his payoff for the current property. That is, P has no interest in learning about the seller.⁸ We also assume that P's payoff in any period in which he does not buy a property is zero.

Fourth, we assume that the parameters are such that the seller's property's expected payoff given a good signal is positive, at least if *P* believes *S* is competent for sure $(q^P = 1)$, and that the property's expected payoff given a bad signal is negative, even if *P* believes *S* is competent for sure $(q^P = 1)$.

Fifth, we assume that whether a property that is sold is actually produced is publicly observable and that, if the property is produced, the revenue generated is public information. This is common in IP markets.

These assumptions allow us to simplify the problem of calculating equilibrium contracts. In particular, it is straightforward to show the following results (proofs and details are in the appendix, section 8):

Lemma 1. P will not produce a property whose signal is bad under any feasible contract.

Lemma 2. A good signal increases both players' probability assessments that *S* is competent, relative to its current value, whereas a bad signal decreases both players' probability assessments that *S* is competent. Finding out for sure that the property is bad (which happens when revenue is zero) decreases both players' probabilities that *S* is competent even more than does a bad signal.

Lemma 3. If it is optimal for S to switch to the secondary market in any given period, it is optimal for her to remain there until the last period.

Lemma 4. No property will ever be bought by P under a contract in which the property certainly (with probability 100%) will not be produced.⁹

Lemma 1 and Lemma 4 reflect the buyer's side. The buyer will only buy properties that he may produce, and if the signal he receives after the transaction is bad, he will refrain from production. Lemma 3 reflects the seller's side. If the seller decides not to participate in the market in some period, she will never participate in the future, since no relevant information is generated in the secondary market. Lemma 2 describes the interaction between buyer and seller- both sides learn from the signal, but the outcome of the production process is much more informative.

With these results in hand, the producer's problem is stated in equations (1-3) below. In words, the producer needs to find a contract in any given period that maximizes his expected payoff subject to the constraints that the present value of the seller's expected utility from payoffs now and in the future is at least as large as the present value of switching to the secondary market, that the cash payment exceeds the minimum payment, and that the contingency payments are non-negative.

⁸If there are many producers but, as we assume here, all information is common knowledge, the free-rider problem may result in the private value of information about a seller being negligible.

⁹ If the cash payment were not constrained to be positive, P might be able to extract a payment from S in return for generating the signal, and a property could be sold under such a contract.

$$\max_{c \ge c_0, K \ge 0} -c - \left[rq^P sk_v + (1-r)(1-q^P s)k_0 \right] + \gamma \left(q^P \right) \left[G(g, q^P)v \quad e \right], \tag{1}$$

subject to

$$G(g,q^{P})v-e \ge G(g,q^{P})k_{v}+\left(1-G(g,q^{P})\right)k_{0}, \qquad (2)$$

and

$$c + \alpha \left[rq^{s}sk_{v} + (1-r)(1-q^{s}s)k_{0} \right] \geq \delta_{t} \left(q^{P}, q^{s} \right).$$

$$(3)$$

We refer to the above problem as *the equilibrium problem*. The objective function, (1), is the producer's expected payoff from the contract. The first two terms give the expected payments to the seller, the cash payment *c* and the expected contingency payments. The third term is the expected revenue from the contract. Here, $G(g,q^P)$ is the probability that the signal is good, *g*, given the producer's beliefs about the seller's competence, q^P , so the term in brackets is the expected profit, given a good signal. The quantity $\gamma(q^P)$ is the producer's probability that the signal will be good, again given his beliefs about the seller's competence, q^P . Constraint (2) is the condition that producing the property is optimal, given a good signal. This is required in view of Lemmas 1 and 2; otherwise no sale occurs. Constraint (3) is the seller's participation constraint, where $\delta_t(q^P, q^S)$ is the smallest *current* payoff in period *t* that the IP contract must provide the seller for her to accept the contract, taking account of the value to her of the secondary market and any future reputational benefits she may receive by accepting. This quantity depends only on the current "state of beliefs," q^P and q^S .

Equation (1) makes it clear that the expected cost to P of a payment k_v to S that is contingent on a successful production is $rq^P sk_v$, while equation (3) shows that the benefit to S of such a payment is $\alpha rq^S sk_v$. Thus, if the condition below holds, the contingency payment is more valuable to S than to P.

$$\alpha q^{S} \ge q^{P}, \tag{4}$$

In that case, the contingency payment should be set as large as possible, subject to the constraint (2) that P will produce the property if he receives the good signal g and subject to S's participation constraint, (3). If the reverse inequality holds, then the contingency payment should be zero.

The same analysis applies to the payment contingent on an unsuccessful production, k_0 , but our assumption that *S* is more optimistic than *P*, $q^S \ge q^P$, implies that the relevant condition for a positive value of this payment cannot be satisfied. That is, *S*'s relative optimism implies that any "bets" between her and *P* should involve *S* betting on *success*, not failure. Consequently, for any equilibrium contract, the contingency payment for an unsuccessful production will be zero.¹⁰ Henceforth, we denote k_v by *k* and drop k_0 from the model.

¹⁰Payments contingent only on production are equivalent to equal positive payments contingent on success and failure. In the screenwriter contracts for the period covered in our empirical tests, the only contingency payments are those contingent on production, despite repeated requests from the screenwriters to include revenue contingencies. In recent years, revenue contingencies have become more frequent, but, given our data, in deriving predictions for our empirical tests, we constrain the two contingency payments to be the same.

To summarize: the important characteristics of the solution to the equilibrium problem are:

- The contingency payment for a successful production is positive if and only if condition (4) holds, and
- The contingency payment for an unsuccessful production is zero.

Thus the key condition for a positive contingency payment is that the seller be more optimistic than the buyer after adjusting for the seller's risk aversion as measured by α . When this condition holds, we say that the seller is *effectively* more optimistic than the buyer. If this is the case, then the seller receives the lowest cash payment needed, generally the minimum payment, and the buyer provides a contingent payment to satisfy the participation constraint. If the seller is effectively less optimistic than the buyer, which will happen in particular if $q^S = q^P$ (since $\alpha < 1$), then the seller receives a cash contract, either the minimum payment or a payment to satisfy the participation constraint if that is larger.

It is important to note that the contracts described above will vary as the game evolves and beliefs change, a key feature of our model.

The remainder of the characterization of the solution of the equilibrium problem consists of a tedious check of which constraints are binding under various conditions and what that implies about the precise values of the contract variables as a function of whether the seller is effectively more or less optimistic than the buyer. The results are not necessary to an understanding of the comparative statics of the model, so this exercise is relegated to the appendix (section 8) where the results are summarized in Table B.

4. Comparative Statics Results

In this section, we trace the effects of varying the exogenous parameters, such as the seller's reputation, her opportunity cost, and the minimum cash payment on the likelihood of a sale and the contract provisions. Our main result is stated in proposition 1. In section 5, we test some of the implications of the model using our screenplay data.

As suggested by our analysis of the equilibrium problem above, a critical element in many of the propositions is the relative magnitudes of αq^{S} and q^{P} which measure the difference between the beliefs of the seller ("discounted" for risk aversion) and those of the buyer. As the expectations of the buyer and seller converge over time, αq^{S} tends to become smaller than q^{P} , since $\alpha < 1$. Thus, we expect condition (4) to be true for less experienced sellers with little or no track record, but not for more experienced sellers. The propositions below use this property to show how contracts for experienced and inexperienced sellers are expected to differ.

Since S's participation constraint, (3), is not binding in all cases, it is difficult to derive comparative statics results in general. It is, however, straightforward for the last two periods. Therefore, in this section we restrict our attention to the two-period case. Two periods provide a good sense of how the contracts evolve over time. Most of the mathematical analysis, including proofs of all propositions in this section, is relegated to the appendix (section 9).

Proposition 1. Contracts over a career path

a) In a multi-period model, as the seller gains experience, she is more likely to receive a cash contract.

b) For either date in a two date model, and for sellers who are effectively less (respectively, more) optimistic than the buyer, those with better reputations (larger q^{P}) will have contracts with larger cash (respectively, contingent) payments than those with worse reputations. Moreover, if a seller's reputation increases from one period to the next, her cash payment also increases.

Discussion: The first part of the proposition says that as both players update their probabilities of competence, the difference of opinions becomes smaller. As a result, because of the seller's risk aversion, cash contracts become more likely. This happens in fact regardless of whether reputation improves or deteriorates, as long a q^s gets closer to q^p , as it will with updating.

We also note that the inequality discussed at the beginning of this section (condition (4)) matters. Intuitively, the second part says that if the buyer is less convinced than the seller that the seller is competent, it is efficient for the buyer to offer the more reputable seller a larger compensation (required to induce a sale) by increasing the contingency payment that will be paid only if the property is produced (i.e., the signal is good).

These results are important, because we predict that contracts offered to beginners will differ from contracts offered to well-known sellers. Sellers who are new to the business are more likely to receive contingent contracts. The proposition also predicts that sellers whose reputations improve over time will enjoy larger cash payments, however, testing this prediction is difficult, because we have few observations of repeat sales by the same seller. Consequently, the implication we take to the data is the positive correlation between cash contracts (or a larger proportion of cash payments, since real life contracts are a function of many variables) and experience.

Proposition 2 describes how contracts and outcomes change as a result of changes in the seller's opportunity cost.

Proposition 2.

As the seller's opportunity cost increases, a sale becomes less likely. If the seller is effectively more optimistic than the buyer, then increases in the opportunity cost lead to an increase in the contingency payment; otherwise cash payments will go up.¹¹

Discussion: This result also implies a difference between inexperienced and experienced sellers in how one should expect IP contracts to respond to a change in the environment. Since inexperienced sellers are likely to be more optimistic than the buyer, the best they can expect when their opportunity cost goes up is higher contingency payments. Experienced sellers on the other hand, whose "effective" optimism is less likely to exceed that of the buyer, are more likely to enjoy larger cash payments. If a sale is made, the "price" (used in what follows to mean the total of cash and contingency payments) will be higher when the opportunity costs are higher.

Our model does not imply a specific correlation between contingent contracts and the probability of production. However, it can generate scenarios (sufficient conditions) under which such correlation exists. Since we would like to take this idea to the data, we can state the following:

Proposition 3.

If either the probability of generating a good property (s) or the quality of the signal (r) or seller optimism (q^s) are sufficiently low, then properties sold under contingent contracts are less likely to be produced than properties sold under all cash contracts.

One additional result sheds some light on the logic of our model and what we expect, although it also cannot be tested directly.

Proposition 4.

¹¹ For period 1, this result requires that the increment in the wage function not be too steep or convex in q. See the proof for a sufficient condition on the wage increment.

a) An increase in the quality of the signal, *r*, keeping reputation and project quality equal, makes a sale more likely, and also affects the cash and contingency payments. In particular, either payment, if it changes, will decrease.

b) An increase in the effectiveness of a competent seller, *s*, increases the probability of a sale. If the seller is effectively more optimistic than the buyer, an increase in *s* will generally decrease the contingency payment, whereas if the seller is effectively less optimistic, the cash payment will decrease instead.

Discussion of part (a): The intuition for the first result is clear. To understand the effect on the payments, it is important to recognize that an increase in signal quality increases the probability that the contingency payment will actually be paid. This probability is the probability of a good signal, given that the property is good, times the unconditional probability that the property is good. An increase in signal quality increases the former but does not affect the latter. Therefore, when the contingency payment will actually receive the seller's participation, since the seller believes it is more likely that she will actually receive the contingency payment. Moreover, an increase in r in the first period also decreases the amount of current compensation required to ensure the seller's participation. This is because the increase in r increases the seller's expected future payments from continuing in the primary market. Thus the buyer can reduce the cash payment when it is not at the minimum while still ensuring the seller's participation.

Discussion of part (b): Again, the first part is straightforward: as properties become better on average, a sale becomes more likely. The intuition for the second part is similar to that of part (a). The key is in recognizing that an increase in the competent seller's ability raises the probability (for both parties) that the property will be produced and the contingency payment will be paid. In the last period, this enables the buyer to reduce the contingency payment when the seller is *effectively* more optimistic than the buyer while keeping its expected value to the seller constant, thus not violating the seller's participation constraint. In the first period, there is a second effect of the increase in *s*, namely the amount of current compensation required to prevent the seller from switching to the secondary market decreases. This is because the increase in *s* increases the seller's expected future payments from continuing in the primary market. Thus, not only can the buyer reduce the cash payment. In the opposite case in which the buyer is effectively more optimistic, the buyer will take advantage of these effects by reducing the cash payment instead.

The model so far is general, and should be applicable to various types of intellectual property sales. We cannot provide comprehensive testing of all the implications of the model. The purpose of the next section is to suggest that the main thrust of the theory is consistent with the properties of contracts observed for screenplay sales.

5. Empirical Implications and Testing

Before turning to a description of the data, we must modify our general propositions of the previous section to account for the fact that, in the screenplay market, contracts rarely exhibit any significant dependence on the degree of success of any eventual film produced from the screenplay. Instead, contingent payments, when present, generally depend only on whether the screenplay is produced. Fortunately, incorporating this fact as a constraint in our model involves few modifications to our predictions.¹² These are as follows:

¹²As mentioned previously, the restriction to production-contingent contracts can be seen as allowing outcome-contingent payments with the added constraint that all such payments be equal. The main effect is to change the criterion for the contingency payment to be more valuable to the seller than to the buyer from $\alpha q^s \ge q^p$

- The statement, "the seller is *effectively* more optimistic than the buyer" must now be interpreted formally as αγ(q^s)≥ γ(q^p) instead of condition (4). Similarly the statement "the seller is *effectively* less optimistic than the buyer" must be interpreted as the reverse inequality.
- Proposition 4: To conclude that the contingency payment decreases with an increase in the quality of the signal, we must make the additional assumption that the seller is sufficiently optimistic. Formally, this assumption is $q^s s > 0.5$.

5.1. Data and background

We chose screenplay sales because, first, contractual data is available, and second, that market provides a close approximation to the assumptions in our model. Our database includes only "spec" screenplays, i.e. original work shopped around when it is done (rather than work for hire, when a studio commissions a script). A screenwriter in our database (seller) typically sells all rights to the property and the studio (buyer) can (and usually does) use other writers to modify the screenplay prior to production. For example, the well-known screenwriter Don Jacoby, who received 1.5 million dollars for his script, told Variety in November 1998, "Not eight words from the original script were in the movie" produced based on his work. Consequently, moral hazard on the part of the seller is absent in this market¹³. Moreover, screenwriters are self-employed individuals and, hence, likely to be risk averse with respect to the income from each screenplay. Studios, on the other hand, are large corporations with a diverse portfolio of screenplays and, hence, likely to be (at least approximately) risk neutral with respect to the income from any given screenplay. Finally, it is quite plausible that neither the screenwriter nor the producer knows the screenwriter's true ability, that both parties learn about the screenwriter's competence by observing the outcome of produced screenplays, and that, in the absence of such evidence, the screenwriter is more optimistic about her competence than is the studio. These are the essential ingredients of our model.

Our data consists of 1269 contracts for screenplay sales that occurred between 1997 and 2003. Our main source of information is the 2003 *Spec Screenplay Sales Directory*, compiled by Hollywoodlitsales.com and used also in Goetzmann et al. (2013). The information provided on each sale usually includes: title, pitch, i.e. a few sentences that can be delivered in writing or orally by a writer or an agent (presumably, the pitch is provided by the agents of the buyer or seller), genre, agent, producer, dateof-sale, and buyer. Sometimes additional information is provided. This additional information (definite or tentative) may identify parties who are interested in the project.¹⁴ We have augmented this base list using similar data found at <u>https://sites.google.com/site/scottdistillery/definitive-spec-script-sales-list</u> and at <u>http://gointothestory.blcklst.com/</u>. These datasets, covering the years 1990-2014, allow us to determine

⁽condition 4(4)) to $\alpha \gamma(q^s) \ge \gamma(q^p)$. Since the function γ is increasing with respect to q and most of the parameters, the comparative statics are largely unaffected.

¹³ Writers may have an option to perform rewrites should they be needed. However, this is a union mandated option, independent of the quality of the script, and the rewrite contract is a new contract.

¹⁴ Additional information may make assessment of the commercial value of the submitted work a bit easier. For example, a comment on "Lightning" by Marc Platt reads: "The writer based screenplay on 1997 novel, 'A Gracious Plenty' which he optioned out of his own pocket. Writer is also a producer." The information may be tentative, e.g., regarding the script "Last Ride," it was noted that, "Ron Howard might direct." In other cases, the information is more definite, e.g., in the notes for the screenplay entitled "Mickey," we find that "Harry Connick Jr. is in talks to star; Hugh Wilson will direct."

more accurately when a sale in our base list is the screenwriter's first sale, and to follow the later career of a writer after a first sale.

We have a purchase price for 787 scripts (62.02% of the total sample). The price may be precise (which we have for 215 scripts, 27.32% of scripts with available price, 16.94% of the total sample). In other cases, *Spec Screenplay Sales Directory* may record an approximate price (572 scripts), such as mid 600's or low 400's. In the latter case, we transform the price range into an estimate (for instance, low five figures is transformed into \$25,000; high six figures is transformed into \$750,000).¹⁵ Prices are adjusted for inflation.¹⁶ WGA (the screenwriters union) sets minimum prices for screenplays, which in early 2004 (somewhat later than the last sale in our dataset) were around \$50,000 for a low budget movie and up to \$90,000 for a high budget film. Most writers are union members, since this is the only way for freelancers to obtain health and retirement benefits. Therefore, as noted, our model is adapted to this institutional reality.

Our main focus is on the type of contract offered. The first type is a fixed payment, noncontingent contract. There are 298 such screenplays in our sample (38%). Alternatively, the screenwriter may be offered a contingent contract (*Contingent*) – 489 of the scripts in our sample fit this description. (Note that there are 10 scripts for which we know the type of contract but not the price.) In a contingent contract the screenwriter receives an initial payment upon contract signing and an additional amount if the script is produced. As noted, in our model a seller may receive a different amount if the production "succeeds" or "fails". The typical screenwriter's contract, however, offers compensation contingent upon production, independent of the revenues of the resulting movie.¹⁷

In our model, reputation and experience are important for determining the type of contracts that writers are awarded. In general, we expect that as reputation and experience increase, the screenwriter will be more likely to receive a cash contract. Empirically, reputation and experience are difficult to disentangle- if you have sold many screenplays presumably you have a good reputation (you have survived in the market). If you have a good reputation, you are likely to sell more. Therefore, we use several proxies that according to our model, should determine the type of contract provided. To measure screenwriter experience we search the Internet Movie Database (IMDb) for the number of scripts previously sold by the screenwriter and produced. If we find no entries, we also search our own database to see if this writer had previously sold any screenplays. The average number of previously produced scripts is 2.07 per screenwriter. The writers of 694 scripts (54.69% of the sample) had not sold any previous work. We thus create a few experience buckets. *MovieExperience* takes the value 0 if the screenwriter has never had any screenplay produced (as per IMDb) or sold (in our database); 1 if the screenwriter has had between 1 and 3 scripts produced (which is the case for 382 scripts, 30.10% of the sample); 2 if between 4 and 10 scripts have been produced (49 scripts, 3.86% of the sample).¹⁸

¹⁵ There is one exception to this rule. Two movies have (non-contingent) prices listed as "eight figures." Since the highest exact price that we have is \$11 million, and we have seen references to record script prices for various studios as being at most in the low seven figures, we have estimated these two prices to be \$10 million. Other than these three, the next highest prices in the database are \$5 million or "mid-seven figures," of which there are 15.

¹⁶ Before doing the analyses, all prices are adjusted to 2003 dollars using the annual average Consumer Price Index factors from the Bureau of Labor Statistics, available at <u>http://www.bls.gov</u>.

¹⁷ Recently, some screenwriters started receiving (small) payments contingent upon the success of the movie, but the agreement that led to these deals was later than the last sale in our database.

¹⁸An ideal experiment from the point of view of our model would be to look at the type of contracts a screenwriter receives over his career. However, even for the few writers who had many scripts produced and sold,

One obvious measure of reputation is awards. We collect the numbers of Oscars and other awards which the writer had won or had been nominated for.¹⁹ Since only 3 writers in our sample had won Oscars prior to selling the screenplays in the sample, we do not use award winner, but define a variable *AnyNom* (*AnyAward*) that takes the value 1 if the screenwriter had been previously nominated for (had won) an award in any of the major festivals tracked by imdb.com: Oscars, Golden Globes, British Academy Awards, Emmy Awards, European Film Awards, and awards from the festivals of Cannes, Sundance, Toronto and Berlin. For 71 scripts, the screenwriter had been nominated in a major festival; in 32 cases, the screenwriter had previously won an award in a major festival; in 27 cases, s/he had been nominated for an Oscar; and for 10 scripts, the screenwriter had previously won an Oscar. As another measure of success, we also construct a variable using the average domestic gross of past films by the writer, *screenwriter competency*. This is of course rough but in a profit oriented industry may be used as a guideline.

We also collect information about the writer's work in other areas. Ex-ante reputation may be enhanced if the writer was known for other enterprises.

We construct the measure as follows: if a screenwriter has sold a screenplay in a certain year, we check to see whether s/he also had acted in or had directed movies, had written for television, had done theater work, or had written books during the ten year period ending with the year of the sale. We use IMDb to look for movie participation, the Internet Broadway Database (IBDB.com) for theater information, and Amazon.com for books. The total number of these opportunities outside screenwriting is the variable *Writer External Experience*. If a screenplay has more than one writer, we use the largest of these values for all the writers, since the most experienced writer is likely to have the most influence on the price paid and on the type of contract offered. For example, in 419 of the screenplays in our data set (33.02% of the sample), at least one writer had participated in at least one television episode as a writer. As another proxy for the writer's opportunity cost, we use a dummy variable, *Writer External Experience Dummy*, which is 1 if the external experience variable is non-zero and 0 otherwise.²⁰

Finally we track the ages of the writers, *WriterAge*. The youngest writer in the sample is Jessica Kaplan, who sold her script in 1995 when she was 16 and a high school student. Age may be another proxy for experience, however for many of the writers in our database, this information is not available.

The Internet Movie Database (IMDB) reports all films produced or that are in production. Our screenplays have led to production of 289 films as of mid-2013. The largest number of films was produced early on, with a trickle going forward after 2006 or 2007.

we do not necessarily have that information, because not all their scripts appear in our data base, as discussed in the text. There is only one writer with 5 screenplays in our data base and a handful with 4. The vast majority only have one screenplay sold in the period covered.

¹⁹ For the importance of awards see Ravid (1999).

²⁰ We only track the creative industries. In other words, the screenwriter's best outside opportunity may be school teaching for example, and we cannot track that. We do not think this is a big issue since most screenwriters tend to be involved in the creative industries rather than in plumbing. A more serious issue is the question of whether we are measuring opportunity cost in the sense of the model or is our measure another proxy for experience. In other words, if a theater director takes on screenwriting he is more likely to be considered a known quantity compared to an unknown finance professor who offers his first script for sale. We address this issue in the interpretation of our results.

Goetzmann et al. (2013) found that script complexity matters.²¹ We use their complexity variables as controls for our regression.

The simplest measure used for the complexity of the script is the number of words in the logline (*LogWords*). Out of 1,269 scripts, the Directory lists the logline (pitch) for 1,218 scripts (95.90%). The average logline description contains 25.92 words and pitches vary from 2 to 96 words. Since the number of words is only a rough approximation, and different types of descriptions require more or fewer words for the same level of complexity, we also use a coarser measure. SoftWords is an index variable, which equals 0 if the logline contains up to 20 words; 1 if it contains between 21 and 30 words; 2 if it contains between 31 and 40 words; and 3 if it contains more than 40 words.²² The logline may be just descriptive or may contain references to existing movies. Eighty-five scripts (6.70% of the scripts for which we have the storyline) mention at least one movie in the story line (29 mention two movies). SoftLogMovies equals 1 if the logline refers to any other movie and zero otherwise. We assume that an analogy or reference to other movies makes the logline more transparent. Additional information is provided for 573 scripts (45.15% of the sample). As discussed earlier, this information may make the script easier to interpret. (*InfoDummy*) is equal to 1 if additional information is provided and zero otherwise. Proxies for the complexity of the script are important control variables for our analysis. Other control variables include genre, the presence of a manager and the identity of the buyer (a large studio or not).

A list of the variables used appears just before the data tables.

5.2. Results

5.2.1. Contract type, screenwriter reputation, and information

Panel A in Table 1 displays the descriptive statistics for the price paid for screenplays, the type of contract (contingent or not), and whether the movie was produced, categorized by values of the other variables. Panel B in Table 1 suggests that experience and past success (reputation) of the writer(s) determine the compensation (as any model would suggest) but these characteristics are also important in determining the type of contract a screenwriter receives as we propose in our empirical implications section. For example, screenwriters who have sold more than 10 scripts (*MovieExperience* =3) obtain average payments that are more than three times as large as those who had previously sold one to three scripts (*MovieExperience* =1). If it is a writer's first movie (*MovieExperience* = 0), he or she receives significantly less money. More importantly for our analysis, writers who have written a larger number of successful screenplays (*MovieExperience* = 3) are much less likely to receive a contingent contract; the probability of receiving a contingent contract for screenwriters with *MovieExperience* = 3 is about 0.38 while for those with *MovieExperience* = 0 it is about 0.62. It seems that the effect of experience on contract design is more pronounced as experience grows, with contingent contracts becoming visibly less prevalent for the most experienced, and as we see below, for the most decorated writers. Previous nomination for any award increases the writer's compensation significantly, as does winning Oscars or

²¹ The model envisions essentially bi-lateral negotiations between the seller and the buyer. This is the most common way that "spec" screenplays (as opposed to commissioned work) are sold. In a handful of cases there are bidding wars, but the number is too small to include it as a variable. As noted, commissioned screenplays (say, sequels) are not included. We should finally note that many writers make a very good living by re-writing other people's scripts. They are not included in this sample for obvious reasons.

²² See Goetzmann et al. (2013) for a discussion of these proxies and the significance of soft information in screenplay sales.

other awards. More importantly for our model, recognition also results in less contingent compensation. For example, having been nominated for an Oscar reduces the probability of getting a contingent contract from 0.62 to 0.46. External experience also decreases the probability of receiving a contingent contract, as is evident in panel B. These facts support our empirical implications. We also note that as experience increases, a larger percentage of cash contracts lead to actual production²³.

The next panel includes screenplay-specific variables. The results suggest that shorter loglines (SoftWords = 0) are associated with higher payments, and a lower probability of a contingent contract. The shortest pitches (Softwords=0) result in a contingent contract in 61% of the cases, whereas the longest pitches (Softwords = 3) result in a contingent contract in 72% of the cases (See Goetzmann et al. (2013) for an extensive discussion of this issue). Similarly, screenplays that provide additional information (InfoDummy = 1) are rewarded for it, and a "transparent script," which is a composite of the two measures, is worth more than a "non-transparent" one.

Table 2 provides summary statistics of our constructed variables as discussed earlier. In the next sub-section, we test some of the propositions.

5.2.2. Tests of some of the propositions

Table 3 speaks to the contract design question. Each panel presents a series of probit regressions (Model 1 – Model 4) estimating the likelihood of receiving a contingent contract. We find that writers are less likely to receive a contingent contract if they have sold more than ten screenplays (*MovieExperience* is 3). The coefficients are always negative, significant in models 1 and 2 and less significant for models 3 and 4. The p-values (.056, .076, .161, .170) increase gradually with model complexity. In Panel B, where we substitute *NumberMovies* for *MovieExperience*, we also find negative coefficients, although only significant at 10% for model 1.

A nomination for an award in any major festival (AnyNom) also reduces the likelihood of receiving contingent contracts, but this coefficient is not significant. We tried various combinations of awards – winning Oscars, nominations for Oscars, etc., and, while they are all negative, none of them is significant. It may be that the small number of Oscar winners and nominated writers makes statistical inferences difficult.²⁴ Importantly, we also find that as the external experience variable is higher, the contract is less likely to be contingent. The coefficients are negative and significant in most specifications. External experience can be viewed as another proxy for reputation, and the results are consistent with Proposition 1.

Complexity (fuzziness) in the pitch is analyzed in more depth in Goetzmann et al. (2013). The results here are consistent with the previous findings. Fuzzier screenplays are more likely to receive a contingent contract. Table 3 (Models 3 and 4 in all three panels) shows that the coefficient of *SoftWords* is positive and significant. A marginal analysis (Table 1, Panel C) shows that the predicted probability of receiving a contingent contract is 0.61 for scripts that contain less than 20 words (*SoftWords*=0), and this probability increases steadily to 0.72 for scripts that contain more than 40 words (*SoftWords*=3). If we use *HighWords*, its coefficient is positive and significant (Model 2 in each panel).

²³ Our stylized model predicts the trend but by construction cannot predict the precise pattern of the evolution of contract design.

²⁴ A variable that measures the average gross of the screenwriter's movies, presumably indicating past success, is not significant, unless it is run without other experience variables. Since much goes into the success of a movie, and gross is not the same as rate of return, this may not be a good proxy (see Ravid (1999)).

Thrillers and comedies seem to be less likely to result in contingent contracts (Models 3 and 4 in Table 3). Desai and Basuroy (2005) note that the most "popular" genres include comedies. It is likely that scripts in some of the more popular genres are perceived to have a higher likelihood of success and hence a lower likelihood of receiving a contingent contract.²⁵

The finding that reputation matters is similar to Banerjee and Duflo (2000) or Luo (2014). Luo (2014) also finds that reputation plays an important role in screenwriters' decisions regarding the stage of development in which a script should be optimally sold.²⁶ There is an interesting contrast between this result and the findings of Chisholm (1997). Chisholm discusses the probability that actors receive a share contract (as opposed to fixed compensation). She finds that more experienced actors are, if anything, more likely to receive share contracts. Chisholm's findings support the Gibbons and Murphy (1992) and Holmström and Milgrom (1992) interpretation of the life cycle of contracts. Experienced actors may need more incentives since their reputation will not be tarnished by one less successful movie, or they may be closer to retirement. However, the contracts Chisholm (1997) investigates are intended to address moral hazard issues as well as risk sharing. In our case, there is no moral hazard, and thus the contract design, which must consider the differential beliefs of buyers and sellers instead, is radically different. Similar to Banerjee and Duflo (2000), we do not seem to find much evidence for risk sharing.²⁷

Table 4 runs a regression of production on various variables, including the type of contract – contingent or non-contingent. There is potential endogeneity, however, between the probability of production and the type of contract. In order to address this issue, we run two stage instrumental variables regressions. *Cont* is an endogenous dummy variable, most often found in the context of treatment models, and we use the "treatreg" command in Stata to carry out the regression.²⁸ Table 4 presents the two stages of the instrumental variables analysis. The bottom panel includes the instrumental variables for contingency, chosen because they were significant in some of the models for *Cont* in Table 3: *Softwords*, *Infodummy*, and *MovieExperience*.²⁹ Focusing on the top panel, which presents the "second stage" regression for *Produced*, we see that the scenario depicted in Proposition 3 can be supported; indeed, contingent contracts are less likely to be produced. The other significant variables are experience and reputation variables; as one can expect, writers with better reputations are more likely to have their work produced; the coefficient of *AnyNom* is positive and significant.³⁰ We can speculate on which of the reasons stated in the proposition leads to the relation we observe, but since these reasons (such as the quality of the signal or the optimism of the seller) are difficult to observe, we suggest that the significance of the coefficient in itself is supportive of the theory.

We performed one additional test which can shed some light on the distinction between our model of reputation building and symmetric learning vs. signaling models which imply better information

²⁵ We repeated all specifications (not reported), with the addition of a *Largestudio* or *Top6* dummy variable. In all cases this variable was positive, but not statistically significant. These results are consistent with large studios using a larger proportion of contingent contracts.

²⁶ Luo (2014) finds that the probability of a sale depends quadratically on a reputation variable.

²⁷ Blumenthal (1988), in a similar framework, analyzes contracts between exhibitors and distributors. Different behavior is predicted and observed in the case of "blind" bidding for films vs. bidding for films that are previewed.

²⁸ Some of the theory for this command can be found in Angrist (2001) and Heckman (1978).

²⁹ Note that the likelihood ratio test makes it clear that *Cont* is indeed an endogenous variable.

³⁰ Again, results with number of movies as an experience variable are almost identical.

on the part of insiders³¹. We considered all screenwriters in our database who had had no previous sales. If contract choice were a signal of ability in a separating equilibrium, then one would expect better writers to signal their ability by taking contingent contracts. This ability should manifest itself in the future (in a typical signaling model, all is revealed in the "second" period). In our model, on the other hand, contingent contracts may reveal optimism, but no superior information. Thus our model suggests that there will be evolution towards more cash contracts as transactions proceed, but there should be no obvious ability signal in the choice of contracts in the "first period".

In order to shed some tentative light on this perspective, we counted the number of screenplays each first time writer has sold during a ten-year period following the initial sale. For the writers whose first sale was in a contingent contract, the average number of additional scripts in the following ten years was .788, while for those with non-contingent contracts the average number was .803. A t statistic is .067 shows that we cannot reject the null hypothesis of equal means at any significance level. This result, which suggests that contingency does not signal future success, is consistent with our model and inconsistent with a signaling perspective.

In summary, although we can only provide partial testing of the many implications of the model, the screenplay data seems consistent with the theoretical analysis. In particular, the empirical findings support our first and possibly most important implication from Proposition 1 that, as experience and reputation increase, contingent contracts become less likely.

6. Conclusions

This paper proposes an explanation of some characteristics of intellectual property contracts based on differences of opinion and reputation building. We show that these features can explain the prevalence of contingencies in IP contracts and the evolution of contracts over a seller's career, as she becomes more experienced. We show that contracts offered to inexperienced, optimistic sellers are very different than contracts that are offered when both sides have become more informed as a result of a series of transactions. The model also shows how the contracts may be expected to respond to variations in other exogenous variables, such as the value of a seller's next best opportunity or the quality of information about the property available to buyers.

We test some of the implications of the model on a large sample of screenplay sales and find that our main predictions are supported.

We believe our framework both as a positive and as a predictive model for other creative industries and IP contracts, such as patents, books, and designs.

³¹ If outsiders are better informed, then signaling models would not predict contingency payments for risk averse insiders.

References

- Adrian, T. and M. Westerfield, 2009, "Disagreement and Learning in a Dynamic Contracting Model," *Review of Financial Studies 22*, 3873-3906.
- Allen, F. and D. Gale, 1988, "Optimal Security Design," Review of Financial Studies 1, 229-263.
- Allen F. and G. H. Faulhaber, 1988, "Optimism Invites Deception," *Quarterly Journal of Economics 103* (2), 397-407.
- Angrist, J. D., 2001, "Estimation of Limited Dependent Variable Models with Dummy Endogenous Regressors: Simple Strategies for Empirical Practice," *Journal of Business & Economic Statistics* 19 (1), 2-16.
- Banerjee, A. V. and E. Duflo, 2000, "Reputation Effects and the Limits of Contracting: A Study of the Indian Software Industry," *Quarterly Journal of Economics 115*, 989-1017.
- Beggs, A. W. 1991, "The Licensing of Patents Under Asymmetric Information" International Journal of Industrial Organization, 10, 171-191.
- Bengtsson, O. and S. Abraham Ravid: (2015) "Location Specific Styles and U.S. Venture Capital Contracting" forthcoming, *Quarterly Journal of Finance*.
- Brunnermeier, M. K., A. Simsek, and W. Xiong, 2014, "A Welfare Criterion for Models with Distorted Beliefs", Working Paper, Princeton University, available at http://scholar.princeton.edu/markus/files/welfare11i.pdf.
- Chevalier, J. A. and D. Mayzlin, 2006, "The effect of word of mouth on sales: online book reviews," *Journal of Marketing Research 43* (3), 345-354.
- Chisholm, D.C., 1997, "Profit Sharing vs. Fixed Payment Contracts Evidence from the Motion Pictures Industry," *Journal of Law, Economics and Organization 13*, 169-201.
- Desai, K. K., and S. Basuroy, 2005, "Interactive Influences of Genre Familiarity, Star Power, and Critics' Reviews in the Cultural Goods Industry: The Case of Motion Pictures," *Psychology and Marketing 22* (3), 203-223.
- Eliashberg, J., S. K. Hui and Z. J. Zhang, 2007, "From Story line to Box Office: A New Approach to Green Lighting Movie Screens," *Management Science* 53 (6), 881-893.
- Filson, D. D. Switzer, and P. Besocke, 2005, "At the Movies: The Economics of Exhibition Contracts," *Economic Inquiry* 43, 354–369.
- Gallini, N.T. and B.D. Wright, 1990, "Technology Transfer Under Asymmetric Information" *Rand Journal of Economics*, Vol. 21 #1, Spring, 147-160.
- Gibbons, R. and L. F. Katz, 1992, "Does Unmeasured Ability Explain Inter-industry Wage Differentials?," *Review of Economic Studies* 59 (3), 515-35.
- Gibbons, R. and K. J. Murphy, 1992, "Optimal Incentive Contracts in the Presence of Career Concerns: Theory and Evidence," *Journal of Political Economy 100* (3), 468-505.
- Gil, R. and F. Lafontaine, 2012, "Using Revenue Sharing to Implement Flexible Pricing: Evidence from Movie Exhibition Contracts," *Journal of Industrial Economics*, June, 187-219.
- Goetzmann, W., S. A. Ravid and R. Sverdlove, 2013, "The pricing of soft and hard information: economic lessons from screenplay sales," *Journal of Cultural Economics* 37 (2), 271-307.
- Graham, J. R., C. R. Harvey, and M. Puri, 2012, "Managerial Attitudes and Corporate Actions," May 22. Available at SSRN: <u>http://ssrn.com/abstract=1432641</u> or <u>http://dx.doi.org/10.2139/ssrn.1432641</u>.

- Greenwald, B. C, 1986, "Adverse Selection in the Labor Market," *Review of Economic Studies 53* (3), 325-347.
- Harris, M. and A. Raviv, 1989, "The Design of Securities," Journal of Financial Economics 24, 255-287.
- Harris, M. and A. Raviv, 1995, "The Role of Games in Security Design," *Review of Financial Studies* 8, 327-367.
- Hong, H. and J. Kubik, 2003, "Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts," *Journal of Finance* 58, 313-351.
- Heckman, J. J., 1978, "Dummy Endogenous Variables in a Simultaneous Equation System," *Econometrica* 46 (6), 931-959.
- Hvide, H. K. and E. G. Kristiansen, 2012, "Management of Knowledge Workers," *Journal of Law and Economics* 55 (4), 815-838.
- Jensen, M. C. and K. Murphy, 1990, "Performance Pay and Top-Management Incentives," *Journal of Political Economy* 98 (2), 225-264.
- Kaplan, S. N. and P. Stromberg, 2003, "Financial Contracting Theory Meets the Real World: An Empirical Analysis of Venture Capital Contracts," *Review of Economic Studies* 70, 281-315.
- Kulatilaka, N. and L. Lin, 2006, "Impact of Licensing on Investment and Financing of Technology Development" *Management Science*, 52(12), 1824-1837.
- Landier A. and D. Thesmar, 2009, "Contracting with Optimistic Entrepreneurs," *Review of Financial Studies 22*, 117-150.
- Leland, H. E. and D. H. Pyle, 1977, "Informational Asymmetries, Financial Structure, and Financial Intermediation," *Journal of Finance 32* (2), 371-387.
- Lerch, J., 1999, 500 Ways to Beat the Hollywood Script Reader: Writing the Screenplay the Reader Will Recommend," New York: Fireside Press.
- Lerner, J., 1995, "Venture Capitalists and the Oversight of Private Firms," *Journal of Finance 50*, 301-318.
- Lerner, J. and R. Merges, 1998, "The Control of Technology Alliances: An Empirical Analysis of the Biotechnology Industry," *Journal of Industrial Economics* 46, 125–156.
- Lovell, E.B., 1968, *Domestic Licensing Practices*, The Conference Board, Experiences in Marketing Management, 18.
- Luo, Hong, 2014, "When to Sell Your Idea: Theory and Evidence from the Movie Industry," *Management Science*, forthcoming.
- Malmendier, U. and J. Tate, 2005, "CEO Overconfidence and Corporate Investment," *Journal of Finance* 60, 2661-2700.
- Malmendier, U. and J. Tate, 2009, "Superstar CEOs," *The Quarterly Journal of Economics 124* (4), 1593-1638.
- Ravid, S. A., 1999, "Information, Blockbusters, and Stars: A Study of the Film Industry," *Journal of Business* 72 (4), 463-492.
- Ravid, S. A. and M. Spiegel, 1997, "Linear Securities as Optimal Contracts in an Environment with an Infinite Number of Bad Projects," *Journal of Financial and Quantitative Analysis 32*, 269-286.
- Russin, R. U. and W. M. Downs, 2012, *Screenplay: Writing the Picture*, 2nd ed., Los Angeles: Silman-James Press.

- Samuelson, L., 1992, "Disagreement in Markets with Matching and Bargaining," *The Review of Economic Studies* 59 (1), 177-185.
- Schankerman, M. and S. Scotchmer, 2001, "Damages and Injunctions in Protecting Intellectual Property," *Rand Journal of Economics 32* (1), 199-220.
- Shavell, S. and T. van Ipersele, 2001, "Rewards vs. Intellectual Property Rights," *Journal of Law and Economics 44* (2), 323-547.
- Topel, R. and M. P. Ward, 1992, "Job Mobility and the Careers of Young Men," *Quarterly Journal of Economics 107* (2), 439-479.
- Varian, H., 2000, "Buying, Sharing and Renting Information Goods," *Journal of Industrial Economics 48* (4), 472-488.
- Varian, H., 2005, "Copying and Copyright," Journal of Economic Perspectives 19 (2), 121-138.
- Von Wachter, T. and S. Bender, 2006, "In the Right Place at the Wrong Time The Role of Firms and Luck in Young Workers' Careers," *American Economic Review 96* (5), 1679-1705.
- Waldman, M., 1984, "Job Assignment, Signaling and Efficiency," *Rand Journal of Economics* 15, 255-267.

Variable Definitions and Data Tables

Script Complexity Variables

- *LogWords* counts the number of words in the script logline.
- *SoftWords* equals 0 if the script logline contains up to 20 words; 1 if it contains between 21 and 30 words; 2 if it contains between 31 and 40 words; and 3 if it contains more than 40 words.
- *HighWords* equals 1 if the script logline contains more than 40 words (*SoftWords* = 3) and 0 otherwise.
- *InfoDummy* equals 1 if additional information about the script is available.
- *TransparentScript* is a script complexity index that equals 1 when the logline contains up to 20 words (i.e. *SoftWords* equals 0), and additional information about the script is available (i.e. *InfoDummy* equals 1).
- SoftGenres equals 1 if the qualified number of genres is greater than 1, and 0 otherwise.
- *SoftLogmovies* equals 1 if the script's logline refers to any other movie, and 0 otherwise.
- SoftIndex = SoftWords + SoftGenres + (1-InfoDummy) + (1-SoftLogMovies) with a value between 0 and 6.

Soft information data are from the Spec Screenplay Sales Directory.

Experience and Reputation Variables

- *NumberMovies* is the number of scripts previously sold by the script's screenwriter.
- *MovieExperience* takes the value 0 if the screenwriter has not previously sold any script; 1 if the screenwriter has previously sold between 1 and 3 scripts, 2 if the screenwriter has previously sold between 4 and 10 scripts, and 3 if the screenwriter has previously sold more than 10 scripts.
- *First Movie* takes the value 1 if the screenwriter has not previously sold any script, and 0 otherwise.
- *Nom Oscar (AwardOscar)* takes the value 1 if the screenwriter has been previously nominated for (won) an Oscar.
- *AnyNom (AnyAward)* takes the value 1 if the screenwriter has been previously nominated for an award in one of the following festivals and competitions: Oscars, Golden Globes, British Academy Awards, Emmy Award, European Film Award, Cannes, Sundance, Toronto, Berlin.
- Screenwriters' competency is the average domestic gross of the screenwriter's past movies.
- *WriterExternalExperienceDummy* is 1 if the writer had acted in or had directed movies, had written for television, had done theater work, or had written books during the ten year period ending with the year in which he sold the screenplay and 0 otherwise. *WriterExternalExperience* is the number of cases of such external employment.

Reputation variables data are from IMDb.

Compensation - Contractual Variables

- *Price* reflects the payment made to the screenwriter when he sells the script. In non-contingent contracts, the screenwriter compensation is fixed (i.e. the screenwriter compensation does not depend on whether the movie is produced or not). In contingent contracts, Price reflects the screenwriter compensation when the movie is not produced. All prices are adjusted from the purchase date to 2003 dollars using the Consumer Price Index.
- *Cont* is a dummy variable that equals 0 if the screenwriter's compensation is fixed; that is, the screenwriter receives a certain salary regardless of whether the movie is produced or not. The variable equals 1 when the contract is contingent and compensation is structured in two steps: the screenwriter receives a certain amount for selling the script and additional payment if the movie is actually made.

• *Produced* is a dummy variable that takes the value 1 if the script has been produced or is in production, and 0 otherwise.

Panel A: Contract Summary Statistics									
		N		Price		Cant	Dere der er d		
		IN	Mean	SD	Median	Cont.	Produced		
Scripts with Contingent Contracts		489	458	385	303	1	0.19		
Scripts with Non-Contingent Contracts		298	915	1578	550	0	0.24		
Panel	B: 5	cript V	Vriter Ex	perience a	and Reputa	tion			
		• •		Price		G (
		N	Mean	SD	Median	Cont.	Produced	cash p	cont p
MovieExperience =	0	434	709	616	575	0.624	0.180	0.197	0.170
	1	251	1011	1441	605	0.629	0.236	0.264	0.219
	2	81	1553	2049	877	0.642	0.250	0.276	0.235
	3	21	2719	2545	2140	0.381	0.316	0.455	0.125
FirstMovie =	0	353	828	1428	535	0.618	0.243		
	1	434	709	616	575	0.624	0.180		
NomOscar =	0	774	603	879	460	0.624	0.223		
	1	13	2290	4249	877	0.462	0.481		
AwardOscar =	0	784	623	1025	464	0.624	0.225		
	1	3	2736	2621	2420	0	0.516		
AnyNom =	0	746	581	787	447	0.625	0.215		
	1	41	1546	2967	565	0.561	0.451		
AnyAward =	0	775	616	1016	460	0.625	0.221		
	1	12	1573	1918	595	0.417	0.516		
WriterExternalExperienceDummy	0	328	491	510	303	0.668	0.171		
	1	459	730	1283	510	0.588	0.253		
		Panel	C: Conti	rol Varial	bles				
		N		Price		Cont	Produced		
		1	Mean	SD	Median	cont.	Trouteeu		
SoftWords =	0	300	672	1280	476	0.607	0.208		
	1	215	624	830	468	0.605	0.251		
	2	142	576	548	520	0.641	0.222		
	3	102	619	1271	293	0.716	0.261		
InfoDummy =	0	513	609	856	468	0.634	0.207		
	1	274	671	1318	447	0.599	0.254		
TransparentScript =	0	657	601	825	452	0.628	0.223		
	1	102	844	1971	510	0.618	0.240		
T 11 4	G								

Table 1: Summary statistics for screenplay price

The **Price** column gives the means, standard deviations, and medians of the **Price** variable (sum of cash and contingency payments) as classified by the variables and values in the first two columns. The **Cont.** and **Produced** columns give the means of those variables, similarly classified. Compensation variables include the price (in thousands of 2003 dollars) paid to the screenwriter (**Price**); which is either the price paid in non-contingent contracts or the initial price paid in contingent contracts; **Cont** is a dummy variable that takes the value 1 when the screenwriter is offered a contingent contract (i.e. a contract in which compensation depends on whether the movie is ultimately produced or not). **Produced** is 1 if the screenplay was produced or is in production and 0 otherwise. **cash p** is the percentage of cash contracts produced and **cont p** is the percentage of contingent contracts produced. We include several screenwriter reputation variables. **MovieExperience** takes the value 0 if the screenwriter has not previously sold any script; 1 if the screenwriter has previously sold between 1 and 3 scripts, 2 if the screenwriter has not previously sold between 4 and 10 scripts. **FirstMovie** takes the value one if the screenwriter has not previously sold any script, and zero otherwise. **NomOscar (AwardOscar)** takes the value 1 if the screenwriter has previously been nominated for (won) an Oscar. **AnyNom (AnyAward**) takes the value 1 if the screenwriter has previously been nominated for (won) an Oscar. **AnyNom (AnyAward**) takes the value 1 if the screenwriter has not previously been nominated (won) for an award in the following festivals: Oscars, Golden Globes, British Academy Awards, Emmy Award, European Film Award, Cannes, Sundance, Toronto, Berlin... **SoftWords** equals 0 if the screent script contains up to 20 words (i.e. **SoftWords** equals 0), and additional information about the script is available. We create a script complexity index, **TransparentScript**, that equals 1 when the log line contains up to

Variable	Ν	Mean	SD	Min	Max
control variables					
LogWords	1218	25.92	13.65	2	96
InfoDummy	1269	0.45	0.50	0	1
SoftLogMovies	1218	0.07	0.25	0	1
SoftWords	1218	1.03	1.06	0	3
Screenwriter Experience and Rep	utation				
NumberMovies	1269	2.07	5.56	0	82
MovieExperience	1269	0.61	0.83	0	3
Firstmovie	1269	0.55	0.50	0	1
NomOscar	1269	0.02	0.14	0	1
AwardOscar	1269	0.01	0.09	0	1
Anynom	1269	0.06	0.23	0	1
Anyaward	1269	0.02	0.15	0	1
WriterAvgRev (\$million)	1099	7.98	25.16	0	242.59
Writer External Experience	1268	2.85	6.02	0	152
Screenplay genres					
Action	1269	0.15	0.36	0	1
Comedy	1269	0.45	0.50	0	1
Drama	1269	0.20	0.40	0	1
Romance	1269	0.14	0.35	0	1
Thriller	1269	0.18	0.38	0	1
Contract variables					
Price (\$thousand)	787	630.88	1039.97	26	15600
Contingent (dummy)	787	0.62	0.49	0	1
Other Control variables					
Writer Age	342	38.24	13.03	14	94
Manager	1269	0.14	0.34	0	1
Largebuyer	1269	.56	.50	0	1
Торб	1269	.38	.49	0	1

Table 2: Descriptive statistics for the variables

LogWords counts the number of words in the script logline. SoftWords equals 0 if the script logline contains less than 20 words; 1 if the script logline contains between 21 and 30 words; 2 if the script logline contains between 31 and 40 words; and 3 if the script logline contains more than 40 words. SoftLogmovies equals 1 if the scripts logline refers to any other movie, and 0 otherwise. InfoDummy equals 1 if additional information about the script is available. TransparentScript equals 1 when the log line contains up to 20 words (i.e. SoftWords equals 0), and additional information about the script is available (i.e. InfoDummy equals 1). SoftGenre equals 1 if the qualified number of genres is greater than 2, and 0 otherwise. NumberMovies measures the number of scripts previously sold by the script's screenwriter and is a key proxy for screenwriter reputation. The genre variables are dummy variables. FirstMovie takes the value 1 if the screenwriter has not previously sold any script, 1 if the screenwriter has previously sold at least one script. MovieExperience takes the value 0 if the screenwriter has not previously sold any script, 1 if the screenwriter has previously sold more than 10 scripts. NomOscar (AwardOscar) takes the value 1 if the screenwriter has previously been nominated for (won) an Oscar. AnyNom (AnyAward) takes the value 1 if the screenwriter has previously been nominated for (won) an Oscar. Solden Globes, British Academy Awards, Emmy Award, European Film Award, Cannes, Sundance, Toronto, Berlin. WriterAvgRev is the average revenue (in millions of dollars) of all movies that were made out of the screenwriter's scripts in the past.

Writer External Experience is the maximum number of outside opportunities (acting, directing, television, theater, books) in the ten years ending in the year of the sale for any of the writers of the screenplay.

The genre variables are dummy variables. Action (Comedy, Drama, Romance, Thriller) takes the value 1 if the script is classified in the "Action" (Comedy, Drama, Romance, Thriller) category by Spec Screenplay Directory, and 0 otherwise. Note that more than one of these genre variables may have the value 1.

Cont, is a dummy variable that equals 0 if the screenwriter's compensation is fixed; that is, the screenwriter receives a certain salary regardless of whether the movie is produced or not. The variable equals 1 when compensation is structured in two steps: the screenwriter receives a certain amount for selling the script and additional payment if the movie is actually made. **Price** is the price paid to the screenwriter (see above).

WriterAge is the age of the first screenwriter. Manager takes the value of 1 if the screenwriter has a manager, and 0 otherwise. Large Buyer is a dummy variable which takes the value of 1 if the buyer is one of the largest studios and top6 is dummy variable if the buyer is one of the six largest studios.

Coefficient (S.E) Coefficient (S.E) Coefficient (S.E) Coefficient (S.E) Coefficient (S.E) Secrementic Experience and Reputation MovieExperience 1 0.01 (0.11) 01 (0.11) 4.02 (0.11) -0.02 (0.11) 2 0.19 (0.16) 0.16 (0.17) 0.14 (0.17) 0.14 (0.17) 3 -0.55* (0.29) -0.55* (0.31) -0.46 (0.32) -0.46 (0.32) -0.416 (0.22) AnyNom -0.12 (0.21) -0.16 (0.22) -0.16 (0.22) -0.16 (0.22) -0.16 (0.22) Screewwriter Competency 0.01 (0.15) 0.23 (0.19) 0.22 (0.19) 0.32 (0.19) SoftWords 0.27* (0.15) 0.118 (0.12) -0.21* (0.14) -0.12 (0.14) HighWords 0.27* (0.15) 0.07* (0.04) 0.07* (0.04) 0.07* (0.04) Infolzammy -0.18 (0.12) -0.21* (0.13) -0.21* (0.14) -0.21* (0.15) SetWords 0.33* (0.18) 0.33* (0.18) 0.32* (0.18) -0.35* (0.17) Dama -0.03 (0.16) 0.32* (0.18) -0.35* (0.17) -0.35* (0.17) Romance 0.33* (0.18) <th>Panel A</th> <th>Model 1</th> <th>Model 2</th> <th>Model 3</th> <th>Model 4</th> <th></th>	Panel A	Model 1	Model 2	Model 3	Model 4	
Accembrite Experience 1 0.01 (0.11) -01 (0.11) -002 (0.11) -002 (0.11) 2 0.19 (0.16) 0.16 (0.17) 0.14 (0.17) 0.14 (0.17) 3 -0.55* (0.29) -0.55* (0.31) -0.46 (0.32) -0.45 (0.32) Writer External -0.22** (0.10) -0.21** (0.10) -0.22** (0.10) -0.12 (0.21) -0.16 (0.22) -0.16 (0.22) Screenvriter Competency 0.0007 (0.002) 0.0007 (0.002) 0.0007 (0.002) 0.0007 (0.002) 0.0007 (0.002) Screenvriter Competency 0.01 (0.15) 0.23 (0.19) 0.23 (0.19) 0.23 (0.19) SoftWords 0.27* (0.15) 0.07* (0.04) 0.07* (0.04) 0.07* (0.04) Screenptog genres -0.12 (0.14) -0.12 (0.14) -0.21 (0.14) -0.21 (0.14) Cumedy -0.35** (0.17) 0.035** (0.17) -0.35*** (0.17) -0.35*** (0.17) Romance -0.35*** (0.17) 0.016 (0.19) 0.024 (0.18) 0.24************************************		Coefficient (S.E)	Coefficient (S.E)	Coefficient (S.E)	Coefficient (S.E)	
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Wind External -0.22 ⁻¹⁺ (0.10) -0.23 ⁺¹⁺ (0.13) Sdfff -0.23 ⁻¹⁺ (0.13) Sdfff Sdfff -0.23 ⁻¹⁺ (0.13) Sdfff Sdfff Sdfff Sdfff Sdfff Sdfff Sdff Sdfff Sdfff	Writer Externel	0 22** (0 10)	0.20* (0.10)	0 21** (0 10)	0 22** (0 10)	
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	AnyNom	-0.22 ** (0.10)	$-0.20^{\circ}(0.10)$	-0.21 (0.10)	-0.22 (0.10)	
Control Variables 0.01 (0.15) 0.23 (0.19) 0.23 (0.19) TransparentScript 0.01 (0.15) 0.23 (0.19) -0.21 (0.14) -0.12 (0.14) HighWords 0.27* (0.15) 0.07* (0.04) 0.07* (0.04) 0.07* (0.04) SoftWords 0.27* (0.15) 0.07* (0.04) 0.07* (0.04) 0.07* (0.04) SoftWords 0.27* (0.15) 0.07* (0.04) 0.07* (0.04) 0.07* (0.04) Action 0.18 (0.16) 0.19 (0.16) Control (0.18) 0.32* (0.18) 0.32* (0.18) Comedy -0.21 (0.14) -0.22 (0.14) -0.22 (0.14) -0.22 (0.14) Drama -0.03 (0.18) 0.32* (0.18) 0.32* (0.18) 0.32* (0.18) Trifler -0.35** (0.17) -0.35** (0.17) 0.18 (0.15) 0.09* (0.10) ManagerDummy 0.0290 0.0577 0.0113 0.0142 Paula Model 1 Model 2 Model 3 Model 4 Sectemwriter Experience and Reputation Number of Novies -0.016 (0.021) -0.016 (0.021) -0.016 (0.021) Sectemwriter Experience and Reputation	Screenwriter Competency		0.12 (0.21)	0.0007 (0.002)	0.0007 (0.002)	
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minoyaminy -0.18 (0.1.2) -0.21* (0.1.3) Screenplay genes 0.18 (0.1.6) 0.19 (0.16) Comedy -0.21 (0.14) -0.22 (0.14) Drama 0.035 (0.16) -0.05 (0.17) Romance 0.33* (0.18) 0.32** (0.17) Other Control Variables -0.35*** (0.17) -0.35*** (0.17) Top6 0.09 (0.10) ManagerDummy 0.18 (0.15) 0.49**** (0.15) Constant 0.43**** (0.07) 0.41**** (0.08) 0.54**** (0.15) 0.49**** (0.16) Number of observations 787 759 756 757 Wald ch ² 0.0103 0.0136 0.0302 0.0322 Pseudo R ² 0.0103 0.0136 0.0302 0.0322 Pseudo R ² 0.018 0.0111 -0.012 (0.011) -0.033 (0.011) Number of Movies -0.018* (0.104) -0.015 (0.011) -0.012 (0.011) -0.033 (0.011) Wire External -0.174* (0.095) -0.164* (0.098) -0.186* (0.100) 0.135 (0.216) Screenwriter Experience and Reputation -0.126 (0.215) <td>SoftWords</td> <td></td> <td></td> <td>0.07* (0.04)</td> <td>0.07* (0.04)</td> <td></td>	SoftWords			0.07* (0.04)	0.07* (0.04)	
Action 0.18 (0.16) 0.19 (0.16) Comedy -0.21 (0.14) -0.22 (0.14) Drama -0.05 (0.16) -0.05 (0.17) Romance 0.33* (0.18) 0.32* (0.18) Thriller -0.35** (0.17) -0.35** (0.17) Other Control Variables 0.18 (0.16) 0.09 (0.10) ManagerDummy 0.43*** (0.07) 0.41*** (0.08) 0.54*** (0.15) 0.49*** (0.16) Number of observations 787 759 756 757 Wald chi ² 10.79 13.66 30.18 32.2 Probability > chi ² 0.0200 0.0577 0.0113 0.0142 Pseude R ² 0.0103 0.0136 0.0302 0.0322 Panel B Model 1 Model 2 Model 3 Model 4 Screenwriter Experience and Reputation -0.015 (0.011) -0.012 (0.011) -0.033 (0.011) Writer External -0.174 (0.095) -0.164* (0.098) -0.186* (0.100) -0.184' (0.100) AnyNom -0.127 (0.135) -0.125 (0.135) Intel (0.125) -0.125 (0.135	IntoDummy			-0.18 (0.12)	-0.21* (0.13)	
Concedy -0.10 (-14) -0.22 (0.14) Drama -0.05 (0.16) -0.05 (0.17) Romance 0.33^* (0.18) 0.32^* (0.18) Thriller -0.35^{**} (0.17) -0.35^{**} (0.17) Other Control Variables 0.39^* (0.18) 0.32^* (0.18) Top6 0.99 (0.10) ManagerDummy 0.18 (0.15) 0.49^{***} (0.16) Number of observations 787 759 756 757 Wald chi ² 0.0290 0.0577 0.0113 0.0142 Probability > chi ² 0.0290 0.0577 0.0113 0.0142 Paudo R ² 0.0126 Coefficient (S.E) Coefficient (S.E) Coefficient (S.E) Coefficient (S.E) Coefficient (S.E) Coefficient (S.E) Screenwriter Experience and Reputation -0.015 (0.011) -0.012 (0.011) -0.033 (0.011) Number of Movies -0.018^* (0.108) -0.016^* (0.009) -0.016^* (0.000) -0.018^* (0.000) AnyNom -0.174^* (0.08) -0.164^* (0.072^* (0.037) 0.072^* (0.037) InfoDummy -0.127 (0.135) $-$	Action			0.18 (0.16)	0 19 (0 16)	
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Romance $0.33*(0.18)$ $0.32*(0.18)$ Thriller $-0.35**(0.17)$ $-0.35**(0.17)$ Other Control VariablesTop6 $0.9(0.00)$ ManagerDummy $0.18(0.15)$ Constant $0.43***(0.07)$ $0.41^{***}(0.08)$ $0.54***(0.15)$ Constant $0.43***(0.07)$ $0.41^{***}(0.08)$ $0.54***(0.15)$ Number of observations 787 759 756 Vald chi^2 0.0290 0.0577 0.0113 0.0142 Pseudo R ² 0.0103 0.0302 0.0322 Pranet BModel IModel ZModel AModel AVerenvriter Experience and Reputation $-0.015(0.011)$ $-0.012(0.011)$ $-0.033(0.011)$ Number of Movies $-0.014^*(0.095)$ $-0.164^*(0.098)$ $-0.186^*(0.100)$ $-0.184^*(0.100)$ AnyNom $-0.174^*(0.095)$ $-0.164^*(0.098)$ $-0.161(0.215)$ $-0.156(0.216)$ Screenwriter Competency $-0.018(0.146)$ $0.252(0.194)$ $0.253(0.194)$ SoftGenres $-0.170(0.135)$ $-0.127(0.135)$ $-0.127(0.135)$ SoftWords $0.279^{**}(0.142)$ $0.001(0.002)$ $-0.212(0.139)$ $-0.218(0.337)$ InfolDummy $-0.337^*(0.138)$ $0.032^*(0.037)$ $0.072^*(0.037)$ InfolDummy $-0.333^*(0.168)$ $0.032^*(0.138)$ $0.224^*(0.178)$ SoftWords $0.279^{**}(0.142)$ $0.033^*(0.178)$ $0.324^*(0.178)$ SoftWords $0.279^{**}(0.142)$ $0.033(0.161)$ $0.944^{**}(0.151)$ Drama $0.044^{***}(0.072)$ 0	Drama			-0.05 (0.16)	-0.05 (0.17)	
Thriller $-0.35^{**} (0.17)$ $-0.35^{**} (0.17)$ <i>Other Control Variables</i> $0.09 (0.10)$ ManagerDummy $0.18 (0.15)$ <i>Constant</i> $0.43^{***} (0.07)$ $0.41^{***} (0.08)$ $0.54^{***} (0.15)$ $0.49^{***} (0.16)$ Number of observations 787 759 756 757 Wald ch ² 0.0290 0.0577 0.0113 0.0142 Pseudo R ² 0.0103 0.0136 0.0302 0.0322 Panel B Model 1 Model 2 Model 3 Model 4 Screenwriter Experience and Reputation Number of Movies $-0.018^{*} (0.193)$ $-0.016 (0.210)$ $-0.033 (0.011)$ Writer External $-0.174^{*} (0.095)$ $-0.164^{*} (0.098)$ $-0.161 (0.215)$ $-0.156 (0.216)$ Screenwriter Competency $-0.018 (0.146)$ $0.252 (0.194)$ $0.253 (0.194)$ SoftWords $0.279^{**} (0.142)$ $-0.127 (0.135)$ $-0.125 (0.135)$ HighWords $0.279^{**} (0.142)$ $-0.333^{**} (0.168)$ $0.324^{*} (0.178)$ TransparentScript $0.018 (0.146)$ $0.252 (0.194)$ $0.218 (0.178)$ SoftWords	Romance			0.33* (0.18)	0.32* (0.18)	
Other Control Variables Top6 0.09 (0.10) ManagerDummy 0.18 (0.15) Constant 0.43*** (0.07) 0.41*** (0.08) 0.54*** (0.15) 0.49*** (0.16) Number of observations 787 759 756 757 Wald chi ² 0.029 0.0577 0.0113 0.0142 Probability > chi ² 0.020 0.0577 0.0113 0.0142 Pseudo R ² 0.0103 0.0136 0.0302 0.0322 Panel B Model I Model Z Model A Model A Number of Movies -0.018* (0.104) -0.015 (0.011) -0.012 (0.011) -0.033 (0.011) Wirter External -0.174* (0.095) -0.164* (0.098) -0.186* (0.100) -0.184* (0.100) AnyNom -0.110 (0.210) -0.0161 (0.215) -0.015 (0.216) Screenwriter Competency -0.018 (0.146) 0.252 (0.194) 0.253 (0.194) SoftGenres -0.127 (0.135) -0.127 (0.135) -0.127 (0.137) InfoDImmmy -0.212 (0.139) -0.212 (0.139) Info Dimemy -0.212 (0.139) <td>Thriller</td> <td></td> <td></td> <td>-0.35** (0.17)</td> <td>-0.35** (0.17)</td> <td></td>	Thriller			-0.35** (0.17)	-0.35** (0.17)	
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Constant $(0.43^{-17}, (0.07)$ $(0.43^{-17}, (0.08)$ $(0.43^{-17}, (0.15)$ $(0.43^{-17}, (0.15)$ Number of observations 787 759 756 757 Wald chi ² 10.79 13.66 30.18 32.2 Probability > chi ² 0.0290 0.0577 0.0113 0.0142 Pseudo R ² 0.0103 0.0136 0.0302 0.0322 Panel B Model 1 Model 2 Model 3 Model 4 Coefficient (S.E) Anole 4 Number of Movies -0.018* (0.104) -0.015 (0.011) -0.012 (0.011) -0.033 (0.011) Writer External -0.174* (0.095) -0.164* (0.098) -0.168* (0.100) -0.184* (0.100) AnyNom -0.110 (0.210) -0.151 (0.215) -0.156 (0.215) -0.125 (0.135) Scheenwriter Competency -0.018 (0.146) 0.252 (0.194) 0.253 (0.194) S	ManagerDummy	0 42*** (0 07)	0 41*** (0 09)	0 5 4 * * * (0 1 5)	0.18 (0.15)	
Number of Movies1071.551.55Probability > chi²0.02900.05770.01130.0142Pseudo R²0.01030.01360.03020.0322Panel BModel IModel 2Model 3Model 4Coefficient (S.E)Screenwriter Experience and ReputationNumber of Movies-0.018* (0.104)-0.015 (0.011)-0.012 (0.011)-0.033 (0.011)Write External-0.174* (0.095)-0.164* (0.098)-0.186* (0.100)-0.184* (0.100)AnyNom-0.174* (0.095)-0.164* (0.098)-0.186* (0.100)-0.156 (0.216)Screenwriter Competency-0.010 (0.021)-0.016 (0.021)-0.016 (0.021)Control VariablesTransparentScript0.018 (0.146)0.252 (0.194)0.253 (0.194)SoftWords0.279** (0.142)SoftWords0.072* (0.037)0.072* (0.037)InfoDummy-0.139 (0.120)-0.212 (0.139)-0.218 (0.139)Drama-0.053 (0.165)-0.054 (0.165)Soreen (0.186)Romance0.337* (0.168)-0.337** (0.168)-0.338** (0.168)Control Variables-0.053 (0.165)-0.054 (0.165)Soreen (0.199) (0.199)Drama0.044**** (0.072)0.416*** (0.079)0.537*** (0.151)0.494*** (0.157)Number of observations787759756756Wald chi²8.2311.0827.8229.97Probability > chi²0.01630.04980.00960.0120<	Number of observations	0.43 *** (0.07)	0.41 (0.08)	0.54*** (0.13)	0.49 (0.16)	
Probability > chi^20.02900.05770.01130.0142Pseudo R^20.01030.01360.03020.0322Panel BModel IModel ZModel 3Model 4Coefficient (S.E)Coefficient (S.E)Coefficient (S.E)Coefficient (S.E)Screenwriter Experience and ReputationCoofficient (S.E)Coefficient (S.E)Coefficient (S.E)Number of Movies-0.018 (0.104)-0.015 (0.011)-0.012 (0.011)-0.033 (0.011)Writer External-0.174* (0.095)-0.164* (0.098)-0.186* (0.100)-0.184* (0.100)AnyNom-0.174* (0.095)-0.164* (0.098)-0.0161 (0.215)-0.156 (0.216)Screenwriter Competency-0.010 (0.02)-0.001 (0.002)-0.001 (0.002)Control Variables-0.127 (0.135)-0.125 (0.125)TransparentScript0.018 (0.146)0.252 (0.194)0.253 (0.194)SoftWords0.279** (0.142)-0.190 (0.120)-0.225 (0.125)Screenplay genresAction0.186 (0.161)0.192 (0.162)-Comedy-0.212 (0.139)-0.0148 (0.178)0.324* (0.178)Drama-0.053 (0.165)-0.054 (0.168)-Control VariablesTop60.082 (0.096)-ManagerDummy0.193 (0.149)0.537*** (0.151)0.494*** (0.157)Number of observations787759756756Wald chi^28.2311.082.7.8229.97Probability > chi^2 <th< td=""><td>Wald chi²</td><td>10.79</td><td>13.66</td><td>30.18</td><td>32.2</td><td></td></th<>	Wald chi ²	10.79	13.66	30.18	32.2	
Pseudo \mathbb{R}^2 0.01030.01360.03020.0322Panel BModel 1Model 2Model 3Model 4Coefficient (S.E)Coefficient (S.E)Coefficient (S.E)Coefficient (S.E)Streenwriter Experience and Reputation-0.015 (0.011)-0.012 (0.011)-0.033 (0.011)Number of Movies-0.018* (0.104)-0.015 (0.011)-0.012 (0.011)-0.033 (0.011)Write External-0.174* (0.095)-0.164* (0.098)-0.186* (0.100)-0.184* (0.100)AnyNom-0.110 (0.210)-0.0161 (0.215)-0.015 (0.216)Screenwriter Competency-0.018 (0.146)0.252 (0.194)0.253 (0.194)Control Variables-0.127 (0.135)-0.125 (0.135)-0.125 (0.135)TransparentScript0.018 (0.146)0.0272* (0.037)0.072* (0.037)SoftWords0.279** (0.142)-0.190 (0.120)-0.225 (0.125)Screenplay genres-0.126 (0.139)-0.212 (0.139)-0.218 (0.161)Action0.186 (0.161)0.192 (0.162)-0.054 (0.165)Romance0.333* (0.178)0.324* (0.178)Thriller-0.337** (0.168)-0.338** (0.168)Control Variables-0.53-756Mumber of observations787759756Number of observations787759756Number of observations787759756Vald chi ² 8.2311.0827.8229.97Probability > chi ² 0.01630.04980.00960.0120Pseudo R ² 0.0079 <t< td=""><td>Probability $> chi^2$</td><td>0.0290</td><td>0.0577</td><td>0.0113</td><td>0.0142</td><td></td></t<>	Probability $> chi^2$	0.0290	0.0577	0.0113	0.0142	
Panel BModel 1Model 2Model 3Model 4Coefficient (S.E)Coefficient (S.E)Coefficient (S.E)Coefficient (S.E)Coefficient (S.E)Screenwriter Experience and ReputationNumber of Movies $-0.018^* (0.104)$ $-0.015 (0.011)$ $-0.012 (0.011)$ $-0.033 (0.011)$ Writer External $-0.74^* (0.095)$ $-0.164^* (0.098)$ $-0.186^* (0.100)$ $-0.184^* (0.100)$ AnyNom $-0.174^* (0.095)$ $-0.164^* (0.098)$ $-0.186^* (0.100)$ $-0.184^* (0.100)$ AnyNom $-0.174^* (0.095)$ $-0.164^* (0.098)$ $-0.186^* (0.100)$ $-0.184^* (0.100)$ AnyNom $-0.174^* (0.095)$ $-0.164^* (0.098)$ $-0.186^* (0.100)$ $-0.194^* (0.002)$ Control Variables $-0.001 (0.002)$ $-0.001 (0.002)$ $-0.001 (0.002)$ Control Variables $-0.127 (0.135)$ $-0.125 (0.135)$ HighWords $0.279^{**} (0.142)$ $-0.127 (0.135)$ $-0.125 (0.137)$ InfoDummy $-0.190 (0.120)$ $-0.225 (0.125)$ Screenplay genes $-0.212 (0.139)$ $-0.218 (0.139)$ Action $0.192 (0.162)$ $-0.053 (0.165)$ $-0.054 (0.165)$ Romance $0.333^* (0.178)$ $0.324^* (0.178)$ Thriller $-0.337^{**} (0.168)$ $-0.338^{**} (0.168)$ Control Variables $0.0416^{***} (0.079)$ $0.537^{***} (0.151)$ $0.494^{***} (0.57)$ Number of observations787759756Wald chi^2 8.23 11.08 27.82 29.97 Probability > chi^2 0.016	Pseudo R ²	0.0103	0.0136	0.0302	0.0322	
Coefficient (S.E)Coefficient (S.E)Coefficient (S.E)Coefficient (S.E)Coefficient (S.E)Screenwriter Experience and ReputationNumber of Movies-0.018* (0.104)-0.015 (0.011)-0.012 (0.011)-0.033 (0.011)Writer External-0.174* (0.095)-0.164* (0.098)-0.186* (0.100)-0.184* (0.100)AnyNom-0.101 (0.210)-0.0161 (0.215)-0.156 (0.216)Screenwriter Competency0.010 (0.010)-0.001 (0.002)-0.001 (0.002)Control Variables-0.127 (0.135)-0.125 (0.135)TransparentScript0.018 (0.146)0.252 (0.194)0.253 (0.194)SoftGenres-0.127 (0.135)-0.125 (0.135)HighWords0.279** (0.142)-0.127 (0.037)0.072* (0.037)InfoDummy-0.190 (0.120)-0.225 (0.125)Screenplay genres-0.186 (0.161)0.192 (0.162)Comedy-0.212 (0.139)-0.218 (0.139)Drama-0.053 (0.165)-0.054 (0.165)Romance-0.337* (0.168)-0.332* (0.178)Thriller-0.337* (0.168)-0.332* (0.168)Control Variables-0.01630.444*** (0.072)0.416*** (0.079)0.537*** (0.151)Number of observations787759756Wald chi ² 8.2311.0827.8229.97Probability > chi ² 0.01630.04980.00960.0120Preduct R-0.01630.04980.00960.0120Preduct R-0.0570.01630.4980.02790.0300Control Va	Panel B	Model 1	Model 2	Model 3	Model 4	
Screenwriter Experience and ReputationNumber of Movies-0.018* (0.104)-0.015 (0.011)-0.012 (0.011)-0.033 (0.011)Writer External-0.174* (0.095)-0.164* (0.098)-0.186* (0.100)-0.184* (0.100)AnyNom-0.110 (0.210)-0.161 (0.215)-0.015 (0.216)Screenwriter Competency-0.001 (0.002)-0.001 (0.002)Control Variables-0.127 (0.135)-0.125 (0.134)TransparentScript0.018 (0.146)0.252 (0.194)0.253 (0.194)SoftGenres-0.127 (0.135)-0.125 (0.135)HighWords0.279** (0.142)0.072* (0.037)0.072* (0.037)InfoDummy-0.190 (0.120)-0.225 (0.125)Screenplay genres-0.186 (0.161)0.192 (0.162)Comedy-0.212 (0.139)-0.218 (0.139)Drama-0.053 (0.165)-0.054 (0.165)Romance0.333* (0.178)0.324* (0.178)Thriller-0.337** (0.168)-0.332** (0.168)Control Variables0.1920.168)Constant0.444*** (0.072)0.416*** (0.079)0.537*** (0.151)0.494*** (0.157)Number of observations787759756756Wald chi ² 8.2311.0827.8229.97Probability > chi ² 0.01630.04980.00960.0120Pseudo R ² 0.00790.01110.02790.0300-value <.05; * p-value <.10	с. <u>ч</u> . г. т. н	Coefficient (S.E)	Coefficient (S.E)	Coefficient (S.E)	Coefficient (S.E)	
Writer Or MoVes-0.018 (0.104)-0.019 (0.011)-0.012 (0.011)-0.0011 (0.011)Writer External-0.174* (0.095)-0.164* (0.098)-0.186* (0.100)-0.184* (0.100)AnyNom-0.110 (0.210)-0.161 (0.215)-0.156 (0.216)Screenwriter Competency-0.001 (0.002)-0.001 (0.002)Control Variables-0.127 (0.135)-0.125 (0.194)TransparentScript0.018 (0.146)0.252 (0.194)0.253 (0.194)SoftGenres-0.127 (0.135)-0.125 (0.135)HighWords0.279** (0.142)-0.190 (0.120)-0.225 (0.125)Screenplay genres-0.190 (0.120)-0.225 (0.125)Action0.186 (0.161)0.192 (0.162)Comedy-0.212 (0.139)-0.218 (0.139)Drama-0.053 (0.165)-0.054 (0.165)Romance0.333* (0.178)0.324* (0.178)Top60.082 (0.096)0.193 (0.149)Constant0.444*** (0.072)0.416*** (0.079)0.537*** (0.151)Number of observations787759756Wald chi ² 8.2311.0827.8229.97Probability > chi ² 0.01630.04980.00960.0120Section R ² 0.00790.01110.02790.300value <.05; * p-value <.10	Screenwriter Experience and Number of Movies	<i>Reputation</i>	0.015 (0.011)	0 012 (0 011)	0.022 (0.011)	
AnyNomControl (0.005)Control (0.005)Control (0.005)Control (0.005)Control (0.005)AnyNom-0.110 (0.210)-0.161 (0.215)-0.156 (0.216)Screenwriter Competency-0.001 (0.002)-0.001 (0.002)Control Variables-0.127 (0.135)-0.125 (0.194)TransparentScript0.018 (0.146)0.252 (0.194)0.253 (0.194)SoftGenres-0.127 (0.135)-0.125 (0.135)HighWords0.279** (0.142)SoftWords0.072* (0.037)SoftWords0.072* (0.037)0.072* (0.037)InfoDummy-0.190 (0.120)-0.225 (0.125)Screenplay genresAction0.186 (0.161)0.192 (0.162)Comedy-0.212 (0.139)-0.218 (0.139)Drama-0.053 (0.165)-0.054 (0.165)Romance0.333* (0.178)0.324* (0.178)Thriller-0.337** (0.168)-0.338** (0.168)Control Variables787759756Top60.082 (0.096)0.193 (0.149)Constant0.444*** (0.072)0.416*** (0.079)0.537*** (0.151)Number of observations787759756Wald chi²8.2311.0827.8229.97Probability > chi²0.01630.04980.00960.0120Pseudo R²0.00790.01110.02790.0300-value <.05; * p-value <.10	Writer External	-0.174* (0.104)	-0.164* (0.098)	-0.186* (0.100)	-0.184* (0.1001)	
Screenwriter Competency-0.001 (0.002)-0.001 (0.002)Control Variables-0.127 (0.135)-0.253 (0.194)TransparentScript0.018 (0.146)0.252 (0.194)0.253 (0.194)SoftGenres-0.127 (0.135)-0.125 (0.135)HighWords0.279** (0.142)0.072* (0.037)0.072* (0.037)InfoDummy-0.190 (0.120)-0.225 (0.125)Screenplay genres-Action0.186 (0.161)0.192 (0.162)Comedy-0.212 (0.139)-0.218 (0.139)Drama-0.053 (0.165)-0.054 (0.165)Romance0.333* (0.178)0.324* (0.178)Thriller-0.337** (0.168)-0.338** (0.168)Control Variables-0.193 (0.149)0.193 (0.149)Constant0.444*** (0.072)0.416*** (0.079)0.537*** (0.151)Number of observations787759756Wald chi ² 8.2311.0827.8229.97Probability > chi ² 0.01630.04980.00960.0120p-seudo R ² 0.00790.01110.02790.0300+value <.05; * p-value <.10	AnyNom		-0.110 (0.210)	-0.161 (0.215)	-0.156 (0.216)	
Control VariablesTransparentScript $0.018 (0.146)$ $0.252 (0.194)$ $0.253 (0.194)$ SoftGenres $-0.127 (0.135)$ $-0.125 (0.135)$ HighWords $0.279** (0.142)$ $0.072* (0.037)$ $0.072* (0.037)$ SoftWords $0.279** (0.142)$ $0.072* (0.037)$ $0.072* (0.037)$ InfoDummy $-0.190 (0.120)$ $-0.225 (0.125)$ Screenplay genres $-0.190 (0.120)$ $-0.225 (0.125)$ Screenplay genres $-0.186 (0.161)$ $0.192 (0.162)$ Comedy $-0.212 (0.139)$ $-0.218 (0.139)$ Drama $-0.053 (0.165)$ $-0.054 (0.165)$ Romance $0.333* (0.178)$ $0.324* (0.178)$ Thriller $-0.337** (0.168)$ $-0.338** (0.168)$ Control Variables $0.494*** (0.072)$ $0.416*** (0.079)$ $0.537*** (0.151)$ Number of observations 787 759 756 Number of observations 787 759 756 Wald chi ² 8.23 11.08 27.82 Probability > chi ² 0.0163 0.0498 0.0096 Probability > chi ² 0.0163 0.0498 0.0096 -value <.05; * p-value <.10	Screenwriter Competency			-0.001 (0.002)	-0.001 (0.002)	
TransparentScript $0.018 (0.146)$ $0.252 (0.194)$ $0.253 (0.194)$ SoftGenres $-0.127 (0.135)$ $-0.125 (0.135)$ HighWords $0.279** (0.142)$ SoftWords $0.072* (0.037)$ $0.072* (0.037)$ InfoDummy $-0.190 (0.120)$ $-0.225 (0.125)$ Screenplay genres $-0.186 (0.161)$ $0.192 (0.162)$ Comedy $-0.212 (0.139)$ $-0.218 (0.139)$ Drama $-0.053 (0.165)$ $-0.054 (0.165)$ Romance $0.333* (0.178)$ $0.324* (0.178)$ Thriller $-0.337** (0.168)$ $-0.338** (0.168)$ Control Variables $0.444*** (0.072)$ $0.416*** (0.079)$ $0.537*** (0.151)$ Number of observations 787 759 756 Wald chi ² 8.23 11.08 27.82 29.97 Probability > chi ² 0.0163 0.0498 0.0096 0.0120 Pseudo R ² 0.0079 0.0111 0.0279 0.0300	Control Variables					
SoftGenres-0.127 (0.135)-0.125 (0.135)HighWords $0.279** (0.142)$ $0.072* (0.037)$ $0.072* (0.037)$ SoftWords $0.072* (0.037)$ $0.072* (0.037)$ $0.072* (0.037)$ InfoDummy $-0.190 (0.120)$ $-0.225 (0.125)$ Screenplay genres $0.186 (0.161)$ $0.192 (0.162)$ Comedy $0.186 (0.161)$ $0.192 (0.162)$ Drama $-0.053 (0.165)$ $-0.054 (0.165)$ Romance $0.333^* (0.178)$ $0.324* (0.178)$ Thriller $-0.337** (0.168)$ $-0.338** (0.168)$ Control Variables $0.193 (0.149)$ $0.193 (0.149)$ Top6 $0.082 (0.096)$ $0.193 (0.149)$ ManagerDummy $0.193 (0.149)$ $0.193 (0.149)$ Variables 787 759 756 Wald chi ² 8.23 11.08 27.82 Probability > chi ² 0.0163 0.0498 0.0096 Probability > chi ² 0.0163 0.0498 0.0096 Provalue <.05, * p-value <.10	TransparentScript		0.018 (0.146)	0.252 (0.194)	0.253 (0.194)	
HighWords $0.279** (0.142)$ SoftWords $0.072* (0.037)$ $0.072* (0.037)$ InfoDummy $-0.190 (0.120)$ $-0.225 (0.125)$ Screenplay genres $0.186 (0.161)$ $0.192 (0.162)$ Comedy $-0.212 (0.139)$ $-0.218 (0.139)$ Drama $-0.053 (0.165)$ $-0.054 (0.165)$ Romance $0.333* (0.178)$ $0.324* (0.178)$ Thriller $-0.337** (0.168)$ $-0.338** (0.168)$ Control Variables $0.444*** (0.072)$ $0.416*** (0.079)$ $0.537*** (0.151)$ Number of observations 787 759 756 Wald chi ² 8.23 11.08 27.82 29.97 Probability > chi ² 0.0163 0.0498 0.0096 0.0120 pseudo R ² 0.0079 0.0111 0.0279 0.0300 p-value < .05; * p-value < .10	SoftGenres			-0.127 (0.135)	-0.125 (0.135)	
SOIT WORDS $0.072* (0.037)$ $0.072* (0.037)$ InfoDummy $-0.190 (0.120)$ $-0.225 (0.125)$ Screenplay genres $-0.190 (0.120)$ $-0.225 (0.125)$ Action $0.186 (0.161)$ $0.192 (0.162)$ Comedy $-0.212 (0.139)$ $-0.218 (0.139)$ Drama $-0.053 (0.165)$ $-0.054 (0.165)$ Romance $0.333^* (0.178)$ $0.324^* (0.178)$ Thriller $-0.337^{**} (0.168)$ $-0.338^{**} (0.168)$ Control Variables $-0.337^{**} (0.168)$ $-0.338^{**} (0.168)$ Top6 $0.082 (0.096)$ $0.193 (0.149)$ Constant $0.444^{***} (0.072)$ $0.416^{***} (0.079)$ $0.537^{***} (0.151)$ Number of observations 787 759 756 Wald chi ² 8.23 11.08 27.82 29.97 Probability > chi ² 0.0163 0.0498 0.0096 0.0120 Pseudo R ² 0.0079 0.0111 0.0279 0.0300 p-value <.05; * p-value <.10	HighWords		0.279** (0.142)			
Introduction Screenplay genres-0.190 (0.120)-0.225 (0.125)Action0.186 (0.161)0.192 (0.162)Comedy-0.212 (0.139)-0.218 (0.139)Drama-0.053 (0.165)-0.054 (0.165)Romance0.333* (0.178)0.324* (0.178)Thriller-0.337** (0.168)-0.338** (0.168)Control Variables0.193 (0.149)0.193 (0.149)Constant0.444*** (0.072)0.416*** (0.079)0.537*** (0.151)0.494*** (0.157)Number of observations787759756756Wald chi ² 8.2311.0827.8229.97Probability > chi ² 0.01630.04980.00960.0120Pseudo R ² 0.00790.01110.02790.300p-value <.05; * p-value <.10	SoftWords			0.072* (0.037)	0.072* (0.037)	
Action $0.186 (0.161)$ $0.192 (0.162)$ Comedy $-0.212 (0.139)$ $-0.218 (0.139)$ Drama $-0.053 (0.165)$ $-0.054 (0.165)$ Romance $0.333^* (0.178)$ $0.324^* (0.178)$ Thriller $-0.337^* (0.168)$ $-0.338^* (0.168)$ Control Variables $-0.337^* (0.168)$ $-0.332^* (0.168)$ Top6 $0.082 (0.096)$ $0.193 (0.149)$ Constant $0.444^{***} (0.072)$ $0.416^{***} (0.079)$ $0.537^{***} (0.151)$ Number of observations 787 759 756 Wald chi ² 8.23 11.08 27.82 29.97 Probability > chi ² 0.0163 0.0498 0.0096 0.0120 Pseudo R ² 0.0079 0.0111 0.0279 0.0300 p-value <.05; * p-value <.10	moDummy			-0.190 (0.120)	-0.225 (0.125)	
Comedy $0.102 (0.102)$ Comedy $-0.212 (0.139)$ Drama $-0.053 (0.165)$ Romance $0.333^* (0.178)$ Thriller $0.333^* (0.178)$ Control VariablesTop6 $0.082 (0.096)$ ManagerDummy $0.444^{***} (0.072)$ O.416^{***} (0.079) $0.537^{***} (0.151)$ Number of observations787759756Wald chi ² 8.23 11.08 27.82 29.97Probability > chi ² 0.0163 0.0079 0.0111 0.0279 0.0300 p-value <.05; * p-value <.10	Action			0.186 (0.161)	0,192 (0 162)	
Drama-0.053 (0.165)-0.054 (0.165)Romance0.333* (0.178)0.324* (0.178)Thriller-0.337** (0.168)-0.337** (0.168)Control Variables-0.337** (0.168)-0.338** (0.168)Top60.082 (0.096)0.193 (0.149)Constant0.444*** (0.072)0.416*** (0.079)0.537*** (0.151)Number of observations787759756Wald chi²8.2311.0827.8229.97Probability > chi²0.01630.04980.00960.0120Pseudo R²0.00790.01110.02790.0300o-value <.05; * p-value <.10	Comedy			-0.212 (0.139)	-0.218 (0.139)	
Romance $0.333*(0.178)$ $0.324*(0.178)$ Thriller $-0.337**(0.168)$ $-0.338**(0.168)$ Control Variables $-0.337**(0.168)$ $-0.338**(0.168)$ Top6 $0.082(0.096)$ ManagerDummy $0.193(0.149)$ Constant $0.444***(0.072)$ $0.416***(0.079)$ $0.537***(0.151)$ $0.494***(0.157)$ Number of observations787759756756Wald chi ² 8.23 11.08 27.82 29.97Probability > chi ² 0.0163 0.0498 0.0096 0.0120 Pseudo R ² 0.0079 0.0111 0.0279 0.0300 $0.value < .05; * p-value < 10$ 0.0079 0.0111 0.0279 0.0300	Drama			-0.053 (0.165)	-0.054 (0.165)	
Thriller $-0.337** (0.168)$ $-0.338** (0.168)$ Control Variables $0.082 (0.096)$ ManagerDummy $0.193 (0.149)$ Constant $0.444*** (0.072)$ $0.416*** (0.079)$ $0.537*** (0.151)$ $0.494*** (0.157)$ Number of observations787759756756Wald chi ² 8.23 11.08 27.82 29.97 Probability > chi ² 0.0163 0.0498 0.0096 0.0120 Pseudo R ² 0.0079 0.0111 0.0279 0.0300 0.0210 0.0279 0.0300 0.0300	Romance			0.333* (0.178)	0.324* (0.178)	
Control Variables 0.082 (0.096) Top6 0.082 (0.096) ManagerDummy 0.193 (0.149) Constant 0.444*** (0.072) 0.416*** (0.079) 0.537*** (0.151) 0.494*** (0.157) Number of observations 787 759 756 756 Wald chi ² 8.23 11.08 27.82 29.97 Probability > chi ² 0.0163 0.0498 0.0096 0.0120 Pseudo R ² 0.0079 0.0111 0.0279 0.0300 o-value <.05; * p-value <.10	Thriller			-0.337** (0.168)	-0.338** (0.168)	
Top6 $0.082 (0.096)$ ManagerDummy $0.193 (0.149)$ Constant $0.444^{***} (0.072)$ $0.416^{***} (0.079)$ $0.537^{***} (0.151)$ $0.494^{***} (0.157)$ Number of observations 787 759 756 756 Wald chi ² 8.23 11.08 27.82 29.97 Probability > chi ² 0.0163 0.0498 0.0096 0.0120 Pseudo R ² 0.0079 0.0111 0.0279 0.0300 p-value <.05; * p-value <.10 0.0111 0.0279 0.0302	Control Variables					
ManagerDummy 0.193 (0.149) Constant 0.444*** (0.072) 0.416*** (0.079) 0.537*** (0.151) 0.494*** (0.157) Number of observations 787 759 756 756 Wald chi ² 8.23 11.08 27.82 29.97 Probability > chi ² 0.0163 0.0498 0.0096 0.0120 Pseudo R ² 0.0079 0.0111 0.0279 0.0300 p-value <.05; * p-value <.10 U U U U	Торб				0.082 (0.096)	
Constant 0.444^{***} (0.072) 0.416^{***} (0.079) 0.537^{***} (0.151) 0.494^{***} (0.157) Number of observations787759756756Wald chi ² 8.2311.0827.8229.97Probability > chi ² 0.01630.04980.00960.0120Pseudo R ² 0.00790.01110.02790.0300p-value <.05; * p-value <.10	ManagerDummy	· · · · · · · · · · · · · · · · · · ·			0.193 (0.149)	
Number of observations 787 759 756 756 Wald chi ² 8.2311.0827.8229.97Probability > chi ² 0.01630.04980.00960.0120Pseudo R ² 0.00790.01110.02790.0300p-value <.05; * p-value <.10	Constant	0.444*** (0.072)	0.416*** (0.079)	0.537*** (0.151)	0.494*** (0.157)	
wate cmo.2511.0627.5229.97Probability > chi²0.01630.04980.00960.0120Pseudo R^2 0.00790.01110.02790.0300p-value <.05; * p-value <.10	Number of observations Wald chi ²	/87 	/59	/56 בפידב	/56	
Pseudo R ² 0.0079 0.0111 0.0279 0.0300 p-value <.05; * p-value <.10	Probability $> chi^2$	ō.23	11.08	27.82	29.97	
p-value <.05; * p-value <.10		0.0163	በ በፈዓጶ	0 0096	0.0120	
	Pseudo R ²	0.0163 0.0079	0.0498 0.0111	0.0096 0.0279	0.0120 0.0300	

Table 3: Probit regression for contingent vs. non-contingent contract

The dependent variable in all panels is **Cont**, a dummy variable that is 0 if the screenwriter's compensation is fixed; that is, he receives a certain salary regardless of whether the movie is produced or not. The variable equals 1 when compensation is structured in two steps: the screenwriter receives a certain amount for selling the script and additional payment if the movie is actually made.

NumberMovies is the number of scripts previously sold by the screenwriter. MovieExperience takes the value 0 if the screenwriter has not previously sold any script; 1 if the screenwriter has previously sold between 1 and 3 scripts; 2 if the screenwriter has previously sold between 4 and 10 scripts; and 3 if the screenwriter has previously sold more than 10 scripts.

WriterExternalExperience is 1 if any of the screenwriters has had any outside opportunities (acting, directing, television, theater, books) in the ten years ending in the year of the sale and 0 otherwise.

ExternalExperienceFirst is an interaction term, the product of WriterExternalExperience and FirstMovie, a dummy variable which is 1 if this is the first movie sold by the writer (**NumberMovies** = 0) and 0 otherwise.

AnyNom (AnyAward) takes the value 1 if the screenwriter has previously been nominated (won) for an award in the following festivals: Oscars, Golden Globes, British Academy Awards, Emmy Award, European Film Award, Cannes, Sundance, Toronto, Berlin. ScreenwriterCompetency is the average domestic gross of all movies that were made out of the screenwriter's scripts in the past in millions of dollars.

TransparentScript, that equals 1 when the log line contains up to 20 words (i.e. SoftWords equals 0), and additional information about the script is available (i.e. InfoDummy equals 1). **SoftGenres** equals 1 if the qualified number of genres is greater than 1, and 0 otherwise. **HighWords** equals 1 if the script logline contains more than 40 words (*SoftWords* = 3) and 0 otherwise. **SoftWords** equals 0 if the script logline contains less than 20 words; 1 if the script logline contains between 31 and 40 words; and 3 if the script logline contains more than 40 words.

The genre variables are dummy variables. Action (Comedy, Drama, Romance, Thriller) takes the value 1 if the script is classified in the "Action" (Comedy, Drama, Romance, Thriller) category by Spec Screenplay Directory, and 0 otherwise. Note that more than one of these genre variables may have the value 1.

Top6 is a dummy variable for the buyer of the screenplay being one of the six largest studios. **ManagerDummy** takes the value of 1 if the screenwriter has a manager, and 0 otherwise.

Compensation, soft information and type of contract data are from the Spec Screenplay Sales Directory. Reputation variables and information regarding whether the movies has been produced is from IMDB.

Dependent variable=Produced	Coefficient (S.E)
Cont.	-0.69*** (0.07)
AnyNom	0.20*** (0.08)
AnyAward	-0.08 (0.13)
Action	0.01 (0.04)
Comedy	-0.03 (0.04)
Drama	0.04 (0.05)
Romance	0.01 (0.04)
Thriller	-0.05 (0.05)
Large Buyer	-0.01 (0.03)
TransparentScript	-0.03 (0.05)
ManagerDummy	0.01 (0.04)
Constant	0.66*** (0.06)
Dependent variable=Cont.	
SoftWords	0.04 (0.02)
InfoDummy	-0.06 (0.08)
MovieExperience	10** (0.05)
Constant	0.33*** (0.07)
Number of observations	746
Wald Chi ²	120.45
$Probability > Chi^2$	0.0000
LogLikelihood	-863.86
LR Test of independence of equation: $\rho = 0$	
Chi ² (1)	13.66
$Probability > Chi^2$ (1)	0.0002
1 < 10	

*** p-value<.01; ** p-value <.05; * p-value <.10

Table 4: Probit Regression for Films Produced

The dependent variable is 1 if the movie was produced and 0 otherwise. The two-stage treatreg process in Stata is used to account for the endogeneity of Cont, which is the dependent variable in the first stage.

Cont is a dummy variable that equals 0 if the screenwriter's compensation is fixed; that is, the screenwriter receives a certain salary regardless of whether the movie is produced or not. The variable equals 1 when compensation is structured in two steps: the screenwriter receives a certain amount for selling the script, and additional payment if the movie is actually made.

MovieExperience takes the value 0 if the screenwriter has not previously sold any script; 1 if the screenwriter has previously sold between 1 and 3 scripts; 2 if the screenwriter has previously sold between 4 and 10 scripts; and 3 if the screenwriter has previously sold more than 10 scripts. **AnyNom** (**AnyAward**) takes the value 1 if the screenwriter has previously been nominated (won) for an award in the following festivals: Oscars, Golden Globes, British Academy Awards, Emmy Award, European Film Award, Cannes, Sundance, Toronto, Berlin. **TransparentScript**, that equals 1 when the log line contains up to 20 words (i.e. *SoftWords* equals 0), and additional information about the script is available (i.e. *InfoDummy* equals 1). **SoftGenres** equals 1 if the qualified number of genres is greater than 1, and 0 otherwise. **HighWords** equals 1 if the script logline contains more than 40 words; 2 if the script logline contains between 31 and 40 words; and 3 if the script logline contains more than 40 words. **SoftLogmovies** equals 1 if the script logline refers to any other movie, and 0 otherwise.

Action (Comedy, Drama, Romance, Thriller) takes the value 1 if the script is classified in the "Action" (Comedy, Drama, Romance, Thriller) category by Spec Screenplay Directory, and 0 otherwise. Note that more than one of these genre variables may have the value 1.

Large Buyer is a dummy variable which takes the value of 1 if the buyer is one of the largest studios. ManagerDummy takes the value of 1 if the screenwriter has a manager, and 0 otherwise.

Appendix

7. Notation

P is the buyer (producer).

- *S* is the seller. *S* can be either competent or incompetent and can produce intellectual property that is either "good" or "bad."
- q_t^i is player *i*'s probability that *S* is competent as of the beginning of period *t*. We refer to q_t^P as *S*'s *reputation* at the beginning of period *t*.

 $\Pr_i(E)$ is the probability that player $i \in \{P, S\}$ assigns to the event *E*.

s is the probability that a competent seller generates a good property in any period.

e is the cost of production of the final good (not including any payments to S).

- *v* is the revenue from the final product. We assume v > e.
- c is an upfront cash payment to S.
- k denotes a payment to S contingent on production. It is k_v if the production succeeds (and revenue is v) and k_0 if the production fails (and revenue is 0).

 $K = (k_0, k_v).$

R is the signal a producer receives after the purchase and before potential production.

r is the probability that P's signal is "correct."

 α is the "risk aversion" parameter – each \$1 contingency payment is worth only α to *S*, where $\alpha < 1$.

G(R,q) is the probability that S's property is good, given P's signal R and the probability q that S is competent.

 $\gamma(q^i) = \Pr_i(R = g|Q)$ is *i*'s probability that *P*'s signal is good, given the state of beliefs *Q*.

 β is S's discount factor.

 $Q = (q^{P}, q^{S})$ is the current state of beliefs about S's competence. q^{P} is S's reputation.

 p_i is player *i*'s distribution of next period's state of beliefs, given this period's state of beliefs, Q.

- $\pi^{i}(Q,k) = \Pr_{i}(\text{current property is produced}|Q,k), i \in \{P,S\}.$
- $U_t(Q)$ is the expected present value of S's current and future income, as of the beginning of period t, given the state of beliefs at date t is Q, assuming equilibrium contracts.
- $w(q^{P})$ is S's per-period payoff in the current and all future periods from participating in the secondary market if her current reputation is q.
- $u_t(q^P)$ is the present value, at the beginning of period t, of S's outside option, given her reputation at date t is q^P . $u_t(q) = w(q)A(\beta, T-t-1)$.

- F(R,q) is next period's probability that *S* is competent, given *P*'s signal, *R*, and this period's belief that *S* is competent, *q*.
- $z(q^i) = \Pr_i(S \text{ is competent} | \text{revenue} = 0, Q).$
- $\hat{V}(Q,c,K)$ denotes *P*'s expected payoff for a contract (c,K) in any period in which the state of beliefs is Q.
- $\delta_t(Q)$ is the smallest *current* payoff in period t that the IP contract must provide the seller for her to participate, taking account of the value to her of the secondary market, $u_t(q^P)$ and any future reputational benefits $\beta \overline{U}_t(Q)$.

8. Solution of the Equilibrium Problem

We solve the problem backwards. First, we analyze *P*'s decision whether to produce a property that he has purchased. Since any upfront cash payment *c* is sunk at this point, given contingency payments *K*, a signal realization *R*, and *P*'s current probability q^P that *S* is competent, *P*'s expected payoff if he produces the property is given by

$$G(R,q^{P})v - e - \left(G(R,q^{P})k_{v} + \left(1 - G(R,q^{P})\right)k_{0}\right),$$
(5)

where $G(R,q) = \Pr(\text{property is good}|R,q)$. Using Bayes' Rule, we have

$$G(R,q) = \frac{r_R qs}{r_R qs + (1 - r_R)(1 - qs)},$$
(6)

where $r_g = r$ and $r_b = (1 - r)$.

P will produce a purchased property, given signal R, if and only if his expected payoff is non-negative. As mentioned in the text, to simplify the problem, we assume

$$G(g,1)v - e > 0 > G(b,1)v \quad e.$$
 (7)

This allows us to prove the following, simple lemma.

Lemma 1. *P* will not produce a property whose signal is bad under any feasible contract.

Proof: Since G is increasing in its second argument, condition (7) implies that G(b,q)v-e<0 for all q. Consequently, our assumption that contingency payments must be non-negative implies that P's expected profit as given in (5) is negative if R = b.

Given Lemma 1 and expression (5), the necessary and sufficient condition for P to produce a property he has purchased is that R = g and

$$G(g,q^{P})v - e \ge G(g,q^{P})k_{v} + \left(1 - G(g,q^{P})\right)k_{0}.$$
(8)

We now characterize the probability of production as perceived by each player. At the beginning of any period, before the signal *R* is observed but after the property is sold (if it is sold), player *i*'s probability that the property is produced depends on the contract (specifically, the contingency payments) and player *i*'s beliefs about *S*'s competence. Let $Q = (q^P, q^S)$ denote the current *state of beliefs* about *S*'s competence, and let

$$\pi^{i}(Q,K) = \Pr_{i}(\text{current property is produced}|Q,K), i \in \{P,S\}$$

denote player *i*'s probability that the current property will be produced, given Q and the contingency payments K. As noted above, if (8) fails, the property will not be produced. If (8) holds, the property will be produced if and only if R = g. Therefore, before the signal is observed, player *i*'s probability of production is given by,

$$\pi^{i}(Q,K) = \begin{cases} 0, \text{ if } G(g,q^{P})v - e < G(g,q^{P})k_{v} + (1 - G(g,q^{P}))k_{0}, \\ \gamma(q^{i}), \text{ if } G(g,q^{P})v - e \ge G(g,q^{P})k_{v} + (1 - G(g,q^{P}))k_{0}, \end{cases}$$
(9)

where $\gamma(q)$ is the probability that *P* receives a good signal, given that *S* is competent with probability *q*, i.e.,

$$\gamma(q) = \Pr(R = g|q) = rqs + (1 - r)(1 - qs).$$
⁽¹⁰⁾

Note that, since r > 1/2, γ is an increasing function of q. Recall that the probability that the seller is competent from the point of view of the producer, q^{P} , is smaller than from the point of view of the seller, q^{S} . Consequently, from *P*'s point of view, the probability of a good signal and hence the probability that the property will be produced (which depends on receiving a good signal), is smaller than from *S*'s point of view.

8.1. Evolution of beliefs about S's competence

In this subsection we calculate how beliefs of the two parties evolve as information arrives.

Let \tilde{Q}' denote the random variable whose realization is next period's state of beliefs. The distribution of \tilde{Q}' , given Q and only whether or not the property is sold and, if so, the contract (i.e., *not* conditional on revenue or the signal), is then given by $\tilde{Q}' = Q$ with probability one if the contract is not sold, and otherwise, the distribution depends on whether (8) is satisfied and whose probabilities are used. If (8) is not satisfied, the property is not produced for sure. Since no property will ever be sold under a contract for which the property is not produced for sure (see lemma 4 below), we do not develop the distribution for \tilde{Q}' in that case.

Lemma 2. Define
$$F(R,q^i) \equiv \Pr_i(S \text{ is competent}|R,Q)$$
 and $z(q^i) = \Pr_i(S \text{ is competent}|\text{revenue} = 0,Q)$. Then

$$1 \ge F(g,q) \ge q \ge F(b,q) \ge z(q) \tag{11}$$

with equalities if and only if q = 1. In particular, the above statements apply to S's reputation (recall, S's reputation is defined to be P's probability that S is competent).

Proof: Using Bayes' Rule,

$$z(q^{i}) = \frac{\Pr(\text{revenue} = 0|S \text{ is competent})q^{i}}{\Pr(\text{revenue} = 0|S \text{ is competent})q^{i} + 1(1 - q^{i})} = \frac{(1 - s)q^{i}}{1 - q^{i}s}.$$
(12)

For player $i \in \{P, S\}$,

$$F(R,q^{i}) = \frac{\Pr(R|S \text{ is competent})q^{i}}{\Pr_{i}(R|Q)}$$

But

$$\Pr(R|S \text{ is competent}) = r_R s + (1 - r_R)(1 - s).$$

Therefore,

$$F(R,q^{i}) = \frac{\left[r_{R}s + (1-r_{R})(1-s)\right]q^{i}}{\Pr_{i}(R|Q)} = \begin{cases} \frac{\left[rs + (1-r)(1-s)\right]q^{i}}{\gamma(q^{i})}, \text{ if } R = g, \\ \frac{\left[(1-r)s + r(1-s)\right]q^{i}}{1-\gamma(q^{i})}, \text{ if } R = b. \end{cases}$$
(13)

It is easy to verify that (11) holds using the formulas in (12) and (13).

If (8) is satisfied, the property is produced if and only if the signal is g. In this case, if the property is produced and is good, the positive revenue reveals that the property is good and, therefore, that S is competent. If the property is produced and is bad, zero revenue reveals that the property is bad and, hence player *i* believes S is competent with probability $z(q^i)$, where z is given by equation (12). If the property is not produced, the signal must have been bad and, therefore, player *i* believes S is competent with probability $z(q^i)$, where *z* is given by equation (12). If the property is not produced, the signal must have been bad and, therefore, player *i* believes S is competent with probability $F(b,q^i)$. We can summarize player *i*'s distribution of \tilde{Q}' , given Q and that the property is sold, denoted $p_i(\tilde{Q}'|Q)$, in the following table.

$ ilde{Q}'$	$p_i(ilde{\mathcal{Q}}' \mathcal{Q})$
(1,1)	$\gamma(q^i)G(g,q^i)=rq^is$
$\left(z\left(q^{\scriptscriptstyle P} ight),z\left(q^{\scriptscriptstyle S} ight) ight)$	$\gamma(q^i) \Big[1 - G(g, q^i) \Big] = (1 - r) (1 - q^i s)$
$\left(F\left(b,q^{P}\right),F\left(b,q^{S}\right)\right)$	$1 - \gamma(q^i)$

Table A

This table gives player *i*'s beliefs, p_i , about next period's state of beliefs, \tilde{Q}' , given this period's state of beliefs, Q, and the fact that the property was sold.

8.2. Equilibrium contracts

Given the assumption that the opportunity cost only changes as a result of events in the primary (IP) market, then, if, in the current period, there is no contract acceptable to both S and P, no contract will be acceptable to both in any future period, since neither player's beliefs about S's competence will change in the interim. We summarize this implication in the following lemma.

Lemma 3. If it is optimal for *S* to participate in the secondary market in any given period, it is optimal to continue to do so until the last period, i.e., *S*'s optimal strategy is to switch to her outside opportunity for the current and all remaining periods.

The present value of S's outside option at period t, given that her reputation at that period is q, is given by

$$u_t(q) = w(q)A(\beta, T-t-1),$$
 (14)

where $A(\beta, n) = \left[\frac{1-\beta^n}{1-\beta}\right]$ is the annuity factor for an annuity that begins immediately (an annuity due),

and lasts *n* periods, including the current period, discounted at rate $\frac{1}{\beta} - 1$.

We now calculate the present value to S of accepting a contract (c, K). Let $U_t(Q)$ denote the present value, at the beginning of period t, of S's current and future income, given Q (reputation) assuming equilibrium contracts. Then the value to S of a contract (c, K), given O, is:

$$\hat{U}_{t}(Q,c,K) \equiv c + \pi^{s}(Q,K)\alpha \Big[G(g,q^{s})k_{v} + (1 - G(g,q^{s}))k_{0}\Big] + \beta E^{s} \Big[U_{t+1}(\tilde{Q}')|Q,K\Big],$$
(15)

where E^i is the expectation using *i*'s beliefs, and \tilde{O}' is the random variable whose realization is next period's state of beliefs and whose distribution is calculated above.

Next let $\hat{V}(Q,c,K)$ denote P's expected payoff for a contract (c,K) in any period in which the state of beliefs is Q. P's expected payoff for the contract is the probability that the property is produced, $\pi^{P}(Q,K)$, times his expected profit (net of the expected contingency payment), given that the property is produced, minus the cash payment, c. Formally,

$$\hat{V}(Q,c,K) = -c + \pi^{P}(Q,K) \Big[G(g,q^{P})(v-k_{v}) - (1-G(g,q^{P}))k_{0} - e \Big].$$

$$(16)$$

Since a necessary condition for the property to be produced is that the signal is good, in equation (16), P's expected revenue, given that the property is produced, is the probability that the property is good, given that the signal is good and P's belief q^{P} that S is competent, i.e., $G(g, q^{P})$, times the revenue if the property is good, v.

Note from equation (16), that when $\pi^{P}(Q,K) = 0$, $\hat{V}(Q,c,K) = -c$, i.e., if the property will not be produced for sure, P's payoff is simply the negative of the cash payment to S. Since we require this cash payment to be positive, any property bought by P under a feasible contract for which the property will surely not be produced yields P a negative payoff. As mentioned in the text, we assume that P's payoff in any period in which he does not buy the property is zero. This yields the following lemma.

Lemma 4. No property will ever be bought by P under a contract in which the property certainly (with probability 100%) will not be produced.

In what follows, therefore, we focus on contracts that satisfy condition (8), i.e., the condition that it is profitable to produce properties that receive a good signal.

We define an equilibrium sequence of contracts as a sequence of contracts $\{c_t(Q), K_t(Q)\}, t \in \{1, \dots, T\}$ such that, for each $t \in \{1, \dots, T\}, (c_t(Q), K_t(Q))$ solves

$$\max_{c \ge c_0, K \ge 0} \hat{V}(Q, c, K), \tag{17}$$

subject to,

$$\hat{U}_t(Q,c,K) \ge u_t(q^P), \tag{18}$$

and

$$U_t(Q) = \hat{U}_t(Q, c_t(Q), K_t(Q)).$$
⁽¹⁹⁾

We refer to the above problem as the equilibrium problem.

Equation (19), together with equation (15), define the sequence $\{U_t(Q)|t \in \{1, ..., T\}\}$ recursively, given $U_{T+1}(Q) \equiv 0$.

Let $V_t(Q)$ denote the value of the solution to the equilibrium problem when the state of beliefs is given by Q. As mentioned above, if the property is not sold, we assume P's payoff is zero in that period. Thus, the property is sold in period t when beliefs are given by Q if and only if $V_t(Q) \ge 0$.

We can characterize the solution of the equilibrium problem fully as follows. Denote $E^{s}[U_{t+1}(\tilde{Q}')|Q,K]$ for *K* which satisfies (8) by $\overline{U}_{t}(Q)$. Note that $\overline{U}_{t}(Q)$ is independent of *K*, since, if the property is produced if and only if R = g, the evolution of beliefs depends only on the signal and revenue (if the signal is good), as can be seen from Table A. Also, define

$$\delta_t(Q) = u_t(q^P) - \beta \overline{U}_t(Q).$$
⁽²⁰⁾

The quantity $\delta_t(Q)$ is the smallest *current* payoff in period *t* that the IP contract must provide the seller for her to participate, taking account of the value to her of the secondary market, $u_t(q^P)$, and any future reputational benefits $\beta \overline{U}_t(Q)$. Using this notation and substituting for $\gamma(q)G(g,q)$ using (6) and (10), we restate the equilibrium problem as

$$\max_{c \ge c_0, K \ge 0} -c - \left[rq^P sk_v + (1-r)(1-q^P s)k_0 \right] + \gamma \left(q^P \right) \left[G\left(g, q^P\right) v \quad e \right], \tag{21}$$

subject to (8) and

$$c + \alpha \left[rq^{s}sk_{v} + (1-r)(1-q^{s}s)k_{0} \right] \geq \delta_{t}(Q).$$

$$(22)$$

As mentioned in the text, if $\alpha q^s \ge q^p$, then it is optimal to make the contingency payment k_v as large as possible subject to (8) and (22). If the reverse inequality holds, then it is optimal to set $k_v = 0$. The same analysis applies to k_0 , but the relevant condition for a positive value of this payment is

$$\alpha \left(1 - q^{s} s\right) \ge 1 - q^{p} s \,. \tag{23}$$

It is easy to check that our assumption $q^{s} \ge q^{p}$ implies that (23) cannot hold. Henceforth, we denote k_{v} by k and drop k_{0} from the model.

Assume the equilibrium problem is feasible, i.e., $G(g,q^{P})v-e \ge 0$. If

$$\delta_t(Q) < c_0, \tag{24}$$

the solution is $c_t(Q) = c_0$, $k_t(Q) = 0$, and $V_t(Q) = -c_0 + \gamma(q^P) [G(g, q^P)v \ e]$. If (24) is not satisfied and $\alpha q^S \ge q^P$, the solution is $c_t(Q) = c_0$,

$$k_t(Q) = \frac{\delta_t(Q) - c_0}{\alpha r s q^S}, \text{ and}$$
(25)

$$V_t(Q) = \gamma(q^P) \Big[G(g, q^P) v - e \Big] - \left[\frac{q^P}{\alpha q^S} \delta_t(Q) + \left(1 \quad \frac{q^P}{\alpha q^S} \right) c_0 \right].$$
(26)

Finally, if $\alpha q^{S} < q^{P}$ and (24) is not satisfied, the solution is $c_{t}(Q) = \delta_{t}(Q) \ge c_{0}$, $k_{t}(Q) = 0$, and $V_{t}(Q) = -\delta_{t}(Q) + \gamma(q^{P}) [G(g,q^{P})v \ e]$. The property will be sold if and only if

$$\gamma(q^{P})(G(g,q^{P})v-e)-c_{0} \ge \max\left\{\delta_{t}(Q)-c_{0},0\right\}\min\left\{\frac{q^{P}}{\alpha q^{S}},1\right\}.$$
(27)

Note that a necessary condition for (27) is that $G(g, q^P)v - e \ge 0$.

Proof. Since both $\gamma(q^{P})$ and $\gamma(q^{S})$ are independent of k, the equilibrium problem is a simple linear program. If the problem is feasible, and (24) is satisfied, then the constraint (22) is satisfied for any $c \ge c_0$ and $k \ge 0$, so the solution is clearly as claimed in the lemma for this case.¹

Suppose the problem is feasible, and (24) is not satisfied. If $\alpha q^{S} \ge q^{P}$, the slope of constraint (22) is steeper than *P*'s iso-profit lines. Consequently, the solution is to choose $c_{t}(Q) = c_{0}$ and $k_{t}(Q)$ such that (22) is binding. This results in $k_{t}(Q)$ given by (25) and $V_{t}(Q)$ given by (26). If $\alpha q^{S} < q^{P}$, the slope of constraint (22) is flatter than *P*'s iso-profit lines. Consequently, the solution is to choose $c_{t}(Q) = \delta_{t}(Q)$, $k_{t}(Q) = 0$, and $V_{t}(Q)$ as claimed for this case.

It is easy to check that, in each case, $V_t(Q) \ge 0$ if and only if (27) is satisfied.

The results are summarized the following table.

¹ In this case, S's participation constraint is not binding.

$\gamma(q^{P})(G(g,q^{P})v-e)-c_{0}$	$\delta_t(Q)$	αq^s	Outcome
$\geq \max\left\{\delta_t(Q) - c_0, 0\right\} \min\left\{\frac{q^p}{\alpha q^s}, 1\right\}$	$\geq c_0$ < c_0	$\geq q^{P}$	$c_{t}(Q) = c_{0}$ $k_{t}(Q) = \frac{\delta_{t}(Q) - c_{0}}{\alpha r s q^{S}}$ $V_{t}(Q) = \gamma(q^{P}) \left[G(g, q^{P}) v - e \right]$ $- \left[\frac{q^{P}}{\alpha q^{S}} \delta_{t}(Q) + \left(1 \frac{q^{P}}{\alpha q^{S}} \right) c_{0} \right]$ $c_{t}(Q) = \delta(Q)$
		$< q^{P}$	$k_{t}(Q) = 0$ $k_{t}(Q) = \gamma(q^{P}) \left[G(g, q^{P}) v - e \right] - \delta_{t}(Q)$
		NA	$c_{t}(Q) = c_{0}$ $k_{t}(Q) = 0$ $V_{t}(Q) = \gamma(q^{P}) \left[G(g, q^{P}) v - e \right] - c_{0}$
$<\max\left\{\delta_{t}(Q)-c_{0},0\right\}\min\left\{\frac{q^{P}}{\alpha q^{S}},1\right\}$	NA	NA	No sale

Table B

This table shows the equilibrium outcomes of a meeting between the seller and the producer at date t, for various contingencies.

9. Proofs of Propositions

As mentioned above, $\overline{U}_2(Q) \equiv 0$, and $\delta_2(Q) = w(q^p) \ge c_0$. For period 1,

$$\delta_{1}(Q) = (1+\beta)w(q^{P}) - \beta\overline{U}_{1}(Q) = w(q^{P}) + \beta \left[w(q^{P}) - E^{S}(w(\tilde{q}^{P})|Q)\right].$$
⁽²⁸⁾

Note that, since w is increasing and convex and S is more optimistic than P, $w(q^P) \le E^S(w(\tilde{q}^P)|Q)$. It follows from (28) that $\delta_1(Q) \le \delta_2(Q) = w(q^P)$ with strict inequality whenever $q^P < q^S$. Using the distribution of \tilde{Q}' calculated above, we have

$$\overline{U}_{1}(Q) = \left[rq^{s}sw(1) + (1-r)(1-q^{s}s)w(z(q^{P})) + (1-\gamma(q^{s}))w(F(b,q^{P})) \right].$$

$$\tag{29}$$

Before proceeding, we state a technical lemma useful for our comparative statics results:

Lemma 5.
$$\frac{\partial}{\partial q^{P}} \delta_{1}(Q) \ge w'(q^{P}) \ge 0$$
,
 $\frac{\partial}{\partial r} \delta_{1}(Q) = -\left[q^{s}s\left(w(1) - w\left(F\left(b, q^{P}\right)\right)\right) + (1 - q^{s}s)\left(w\left(F\left(b, q^{P}\right)\right) - w\left(z\left(q^{P}\right)\right)\right)\right] \le 0$, and
 $\frac{\partial}{\partial s} \delta_{1}(Q) = -q^{s}\left[r\left(w(1) - w\left(F\left(b, q^{P}\right)\right)\right) + (1 - r)\left(w\left(F\left(b, q^{P}\right)\right) - w\left(z\left(q^{P}\right)\right)\right)\right] \le 0$.

Proof. For the first result, from (28), it suffices to show that $\frac{\partial}{\partial q^P} E^s \left(w(\tilde{q}^P) | Q \right) \le w'(q^P)$. Now

$$\frac{\partial}{\partial q^{P}}E^{s}\left(w\left(\tilde{q}^{P}\right)|Q\right) = w'\left(z\left(q^{P}\right)\right)\left(1-r\right)\left(1-q^{s}s\right)z'\left(q^{P}\right) + w'\left(F\left(b,q^{P}\right)\right)\left(1-\gamma\left(q^{s}\right)\right)\frac{\partial F\left(b,q^{P}\right)}{\partial q^{P}}.$$

It is easy to check that, since $q^{P} \le 1$, $z'(q^{P}) \le \frac{1}{1-q^{P}s}$ and $\frac{\partial F(b,q^{P})}{\partial q^{P}} \le \frac{r}{1-\gamma(q^{P})}$. Also, since

 $q^{P} \ge F(b,q^{P}) \ge z(q^{P})$, and w is convex, $w'(q^{P}) \ge w'(F(b,q^{P})) \ge w'(z(q^{P}))$. Therefore

$$\frac{\partial}{\partial q^{P}} E^{s} \left(w \left(\tilde{q}^{P} \right) \middle| Q \right) \leq w' \left(q^{P} \right) \left[\frac{(1-r)(1-q^{s}s)}{1-q^{P}s} + \frac{r \left(1-\gamma \left(q^{s} \right) \right)}{1-\gamma \left(q^{P} \right)} \right]$$
$$\leq w' \left(q^{P} \right) (1-r+r), \text{ since } q^{P} \leq q^{s},$$
$$= w' \left(q^{P} \right).$$

This completes the proof of the first statement.

For the second statement,

$$\begin{aligned} &\frac{\partial}{\partial r}\delta_{1}(Q) = -\beta \frac{\partial}{\partial r}E^{s}\left(w\left(\tilde{q}^{P}\right)\right)Q\right) \\ &= -\beta \Big[q^{s}sw(1) - (1 - q^{s}s)w(z(q^{P})) - (q^{s}s - (1 - q^{s}s))w(F(b, q^{P}))\Big] \\ &= -\beta \Big[q^{s}s(w(1) - w(F(b, q^{P}))) + (1 - q^{s}s)(w(F(b, q^{P})) - w(z(q^{P})))\Big].\end{aligned}$$

The inequality follows from the fact that $1 \ge F(b, q^P) \ge z(q^P)$ and w is increasing.

For the third statement,

$$\begin{aligned} &\frac{\partial}{\partial s}\delta_{1}(Q) = -\beta\frac{\partial}{\partial s}E^{s}\left(w\left(\tilde{q}^{P}\right)\right)Q \\ &= -\beta\left[rq^{s}w(1) - (1-r)q^{s}w\left(z\left(q^{P}\right)\right) - \left(rq^{s} - (1-r)q^{s}\right)w\left(F\left(b,q^{P}\right)\right)\right)\right] \\ &= -\beta\left[rq^{s}\left(w(1) - w\left(F\left(b,q^{P}\right)\right)\right) + (1-r)q^{s}\left(w\left(F\left(b,q^{P}\right)\right) - w\left(z\left(q^{P}\right)\right)\right)\right)\right] \end{aligned}$$

Again, the inequality follows from the fact that $1 \ge F(b, q^P) \ge z(q^P)$ and w is increasing.

Proposition 1.

a) In a multi-period model, as the seller gains experience, he is more likely to receive a cash contract.

b) For either date in a two date model, and for sellers who are effectively less (respectively, more) optimistic than the buyer, those with better reputations (larger q^{P}) will have contracts with larger cash (respectively, contingent) payments than those with worse reputations. Moreover, if a seller's reputation increases from one period to the next, her cash payment also increases.

Proof. For part (a) Bayesian updating implies that, as the period game is played repeatedly, beliefs of the two players tend to converge. Thus for more experienced sellers it is more likely that $\alpha q^{S} < q^{P}$, which, as seen in Table B, implies that the contract is a cash contract. For inexperienced sellers, it is more likely that $\alpha q^{S} \le q^{P}$, which, as seen in Table B, implies that the contract is contract is contingent (at least if the minimum current period payment to the seller required for her to participate exceeds the minimum cash payment).

For part (b), consider date 2. Assuming the property is sold, for q^P such that $\alpha q^S \ge q^P$, an increase in q^P increases the contingency payment (Since $\delta_2(Q) = w(q^P) \ge c_0$) but has no effect on the cash payment, while the opposite is true if $\alpha q^S < q^P$. This latter condition is of course true if seller and buyer have the same probability of competence $(q^P = q^S)$.

Now consider date 1. Since $\delta_1(Q)$ is increasing in q^P (Lemma 5), if $\delta_1(Q) \ge c_0$, the results are the same as for date 2. If $\delta_1(Q) < c_0$, a change in q^P has no effect on either payment, unless it reverses the inequality between $\delta_1(Q)$ and c_0 . In that case, again the results are the same as for date 2.

Finally, consider the comparison between c_1 and c_2 . If *P* buys the property at date 2 and $q_2^P \ge q_1^P$, then $q_2^P = q_2^S = 1$, so $\alpha q^S < q^P$, and $c_2(Q_2) = w(1)$ (see Table B). On the other hand, $c_1(Q_1)$ is

either c_0 or $\delta_1(Q_1)$ (Table B). But $w(1) > c_0$ (from our assumptions on w), and $\delta_1(Q_1) \le w(q_1^P) \le w(1)$, with strict inequality if $q_1^P < 1$ (see the discussion following equation (28)).

Proposition 2. As the seller's opportunity cost increases, a sale becomes less likely. If the seller is effectively more optimistic than the buyer, then increases in the opportunity cost lead to an increase in the contingency payment; otherwise cash payments will go up.

Proof. First consider period 2. Suppose S's secondary-market wage function, w, increases for all q^P . This reduces V_2 , as can be seen from Table B (recall $\delta_2(Q) = w(q^P) \ge c_0$), making a sale less likely. When a sale occurs, if $\alpha q^S \ge q^P$, an increase in w increases the contingency payment but has no effect on the cash payment. If $\alpha q^S < q^P$, an increase in w increases the cash payment but has no effect on the contingency payment.

Now consider period 1. Suppose S's secondary-market wage function increases from w(q) to w(q)+d(q), where d(q)>0 for all q. If this increase results in an increase in $\delta_1(Q)$ for all Q, then the result for period 2 goes through. The change in $\delta_1(Q)$ due to the increase in S's secondary-market wage is given by

$$d(q^{P})-\beta\left[E^{S}\left(d\left(\tilde{q}^{P}\right)|Q\right)-d(q^{P})\right].$$

Clearly, this expression is positive if *d* is not "too" steep or convex. A sufficient condition is that $\beta d(1) \le (1+\beta) \min_{q \in [0,1]} d(q)$.

Proposition 3

If either the probability of generating a good property (s) or the quality of the signal (r) or seller optimism (q^s) are sufficiently low, then properties sold under contingent contracts are less likely to be produced than properties sold under all cash contracts.

Proof. First, recall that the <u>true</u> probability of production for a property sold by a seller is $\gamma(q) = \Pr(R = g|q) = rqs + (1-r)(1-qs)$, where q is the seller's true competence probability. To say anything about the empirical production probability, we need to take a stand on the true competence probability.

Consider two sellers who have sold properties, seller "C" (for "contingent") under a contract with $k_t(Q) > 0$ and seller "N" (for "non-contingent") under a contract with $k_t(Q) = 0$. The reason why seller C has a contingent contract and seller N does not is that $\alpha q^S > q^P$ and $\delta_t(Q) > c_0$ for seller C, but one or both of these inequalities is reversed for seller N.

Lower *s* increases $\delta_t(Q)$ (Lemma 5) but reduces $\gamma(q)$. Consequently, sufficiently small *s* can account for the difference in contracts. Lower *r* also increases $\delta_t(Q)$ (Lemma 5) but reduces $\gamma(q)$ if qs > 0.5. Consequently, sufficiently small *r* together with qs > 0.5 can account for the difference in contracts. Finally, lower q^s reduces $\gamma(q)$, if $q = q^s$, so that could account for the difference.

Proposition 4.

4a) An increase in r (the quality of the signal), keeping reputation and project quality equal, makes a sale more likely, and also affects the cash and contingency payments. In particular, either payment, if it changes, will decrease.

Proof. Using $q^{s} \ge q^{p}$, $r \in (0.5,1)$, e < v, and $q^{p} \le 1$ it is straightforward to check that $\gamma(q^{p})[G(g,q^{p})v-e]$ is increasing in *r*, and $\frac{q^{p}}{\alpha q^{s}}$ is independent of *r*. Since $\delta_{t}(Q)$ is (weakly)

decreasing in r for both t (see Lemma 5), it follows that V_t is increasing in r for both t. Thus, an increase in signal quality makes a sale at either date more likely.

For date 2, it is clear from Table B that an increase in signal quality has no effect on the cash payment. If $\alpha q^{S} \ge q^{P}$, an increase in *r* decreases the contingency payment (recall δ_{2} is independent of *r*). If $\alpha q^{S} < q^{P}$, an increase in *r* has no effect on either payment.

For date 1, it is clear from Table B that an increase in signal quality reduces the cash payment when the cash payment equals $\delta_1(Q)$ (i.e., when $\alpha q^s < q^p$ and $\delta_1(Q) > c_0$) and otherwise has no effect on the cash payment. When a sale occurs for $\alpha q^s \ge q^p$ and $\delta_1(Q) > c_0$, an increase in signal quality decreases the contingency payment. In all other cases, a change in signal quality has no effect on the contingency payment.

4b. An increase in *s* (the effectiveness of a competent seller) increases the probability of a sale. If the seller is effectively more optimistic than the buyer, an increase in *s* will generally decrease the contingency payment, whereas if the seller is effectively less optimistic, the cash payment will decrease instead.

Proof. The effect of a change in *s* is very similar to that of a change in *r*. Again, it is straightforward to check that $\gamma(q^P)[G(g,q^P)v-e]$ is increasing in *s*, and $\frac{q^P}{\alpha q^S}$ is independent of *s*. Since $\delta_t(Q)$ is (weakly) decreasing in *s* for both *t* (see Lemma 5), it follows that V_t is increasing in *s* for both *t*. Thus, an increase in the ability of a competent seller makes a sale at either date more likely.

If $\alpha q^{s} \ge q^{p}$, an increase in *s* has no effect on the cash payment but reduces the contingency payment. If $\alpha q^{s} < q^{p}$, an increase in *s* has no effect on the contingency payment or the cash payment at date 2.

For date 1, it is clear from Table B that a change in *s* reduces the cash payment when the cash payment equals $\delta_1(Q)$ ($\alpha q^s < q^p$ and $\delta_1(Q) > c_0$) and otherwise has no effect on the cash payment. When a sale occurs for $\alpha q^s \ge q^p$ and $\delta_1(Q) \ge c_0$, an increase in *s* decreases the contingency payment. If $\alpha q^s < q^p$ a change in *s* has no effect on *k*. Finally, an increase in *s* may reverse the inequality $\delta_1(Q) \ge c_0$. In that case, either the contingency payment remains at zero or it falls to zero.

10. Selling a Screenplay – The Institutional Background

One can register a screenplay with the Writers Guild of America (WGA); however, a writer will need an agent in order to submit a screenplay to a studio or production company. Getting an agent may not be trivial: quite a few agencies do not accept unsolicited manuscripts,² and represent only people who are referred by people they know. The agent may submit a screenplay to be evaluated by a production company. Most major studios have several layers of screening before a script ends up in the hands of someone who can make a purchase decision. WGA sets minimum prices for screenplays, which in early 2004 (somewhat later than the last sale in our dataset) were around \$50,000 for a low budget movie and up to \$90,000 for a high budget film. However, a purchase (which is when the screenplay appears in our data), even at a very high price, is no guarantee of production. It may still take a while for anything to happen. First, screenplays are "developed," that is, changed, re-written and adapted to both the creative and pragmatic (budget) requirements of the purchasing entity.³ In our model this corresponds to the "signal" received. Then, even if everybody is happy with the final write-up, there may not be a studio that is willing to finance and distribute the film.⁴

²See WGA.org.

³ A playwright contractually controls a play written for the theater. No one is allowed to change her lines. In the movie business this is very different.

⁴ The film industry boasts a large number of people who make a very nice living writing screenplays, but rarely if ever having anything actually produced.