When to Sell Your Idea:

Theory and Evidence from the Movie Industry

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Abstract

I study a model of investment and sale of ideas and test its empirical implications using a novel data set from the market for original movie ideas. Consistent with the theoretical results, I find that buyers are reluctant to meet unproven sellers for early-stage ideas, which restricts sellers to either developing the ideas fully (to sell them later) or abandoning them. In contrast, experienced sellers can attract buyers at any stage and they sell worse ideas sooner and better ideas later. These results have important managerial implications for buyers and sellers and show that, in such contexts, policy interventions that discourage buyer participation—such as stronger intellectual-property protection—may diminish the market for ideas and hurt inexperienced sellers.

1 Introduction

A vibrant market for ideas can improve the efficiency of the innovation process by facilitating specialization and avoiding duplicate investments in complementary assets (Teece (1986); Arora et al. (2001); Gans and Stern (2003)). But the market for ideas is full of frictions that make it difficult for innovators to sell their ideas profitably. Perhaps the most fundamental of these frictions is the paradox of disclosure (Arrow (1962)):

It is difficult for a potential buyer to assess the value of an idea before disclosure, but once the idea is known, the buyer has little incentive to pay.[1]

The previous literature typically takes ideas as given and focuses on the contracting issue, asking how innovators can capture value when intellectual-property protection is incomplete (e.g., Bhattacharya and Ritter (1983); Gallini and Wright (1990); Anton and Yao (1994, 2002); Baccara and Razin (2006); Biais and Perotti (2008)). In this paper, I abstract from the contracting issue but allow the seller to choose the completeness of his idea. The gradual development of ideas, products, and services is an important characteristic of many development processes. At each stage, innovators need to decide whether to bring the idea to market or to invest in it further. Selling earlier in the process avoids sunk costs, and it may be more efficient if the downstream firm has a cost advantage in development or better information about demand.[2] However, more-fully-developed ideas typically enjoy better intellectual property rights protection, providing an incentive to delay the sale. For example, a complete manuscript enjoys stronger copyright protection than a book proposal; technological knowledge is more secure with than without a patent; and a start-up with functioning products or services is better protected than a mere business concept.

The innovator's decision to sell is intertwined, of course, with the buyer's incentive to consider an acquisition. Getting buyers to listen is challenging because the costs of evaluating an idea can be substantial, and there is often significant legal risk over the unauthorized use of the disclosed knowledge (Anton and Yao (2008)). The buyer's hesitation to consider the seller's idea provides a powerful incentive to delay a sale. Both parties understand that development is costly. As a result, continued investment by the seller credibly signals his private information about the idea's potential, which, in turn, influences both the buyer's willingness to listen and the transaction price.

To better understand the seller's decision of when to bring his idea to market, I develop a model in which the seller has a nascent idea and decides to sell it now, develop it further and sell later, or simply drop it. The model has the following elements. First, before the idea is disclosed, the buyer observes something about the seller (such as his track record) that helps her assess the idea's expected quality. However, the seller still possesses some private information about this particular idea's value that is impossible to credibly convey without disclosure. Second, the seller's ability to appropriate rent increases as the idea is further developed. Third, the buyer can decide whether or not to listen to the idea. Relative to the idea's expected, the buyer's cost of participation is non-trivial. Finally, the buyer provides extra information about demand

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[1]Other applications of the Arrow problem include the employee's choice of selling his invention to his employer or leaving the firm to form a start-up (Anton and Yao (1995); Hellmann (2007b)); and how concerns about employee expropriation of the firm's private knowledge shape the organizational structure (Rajan and Zingales (2001); Hellmann and Perotti (2011)).

[2]See Pindyck (1991) for an overview of the literature on investment under uncertainty and Roberts and Weitzman (1981) for an application of the problem in sequential R&D, in which they derive the option value of information.

that is valuable to know before the big investment occurs.

The main prediction of the model is that the likelihood of a later-stage sale is non-monotonic with respect to the seller's observable quality: Sales from the best and worst sellers are more likely than sales from intermediate-quality sellers to be fully-developed. Because it is costly for the buyer to participate, not all sellers get a chance to even disclose—especially inexperienced ones trying to sell earlier. Therefore, the likelihood of a later-stage sale is high for low-quality sellers, even though they are most likely to sell earlier if given the chance. Once the seller is good enough to obtain an audience for ideas of any stage, this likelihood drops. These sellers follow a threshold strategy: Sell better ideas later and worse ideas earlier. Note that the choice of the sale stage signals the seller's private information, which influences the buyer's decision to learn more about the idea.[3] Eventually, the likelihood of a later-stage sale increases again because top sellers want to sell later more often in order to capture more surplus.

The market for original movie ideas in Hollywood provides an interesting testing ground for the model. First, the choice here is simple and discrete: The writer sells an idea to a studio either as a storyline (*pitch*) or as a complete script (*spec*).[4] Second, studios specialize in financing, developing and distributing movies; hence, it is valuable to have information about the studio's demand and its assessment of an idea before making substantial investments. Third, the legal protection for ideas with a complete script is generally stronger than that for ideas without one. Finally, in many other settings, quality is either not well-defined or it is hard to obtain performance data. In this industry, we can observe the outcome of a project because the life cycle of a movie is short, and this provides valuable information on an idea's quality.[5]

The primary data come from *Done Deal Pro*, an internet database that tracks idea transactions in Hollywood on a daily basis.[6] The analysis sample contains 1,847 ideas sold in Hollywood between 1997 and 2005, about 55% of which are specs (i.e., later-stage sales). Complementing the sales data with data from *IMDb* and *TheNumbers*, I also observe the writer's industry experience and the outcome (e.g., whether it is eventually released in theaters and, if so, its box office revenues).

The empirical results are consistent with the theory. Empirically, I measure the writer's observable quality using his major writing credits in the previous five years. I find that the likelihood of a spec (i.e., later-stage) sale is highest for writers with zero credits or with three or more credits, while this likelihood

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[3]My model is different from others in that the signaling effect is on the buyer's meeting decision, not on the eventual sale price, because information is complete after the disclosure.

[4]Examples of pitches include 27 Dresses, Mr. and Mrs. Smith, The Last Samurai and The Wedding Crashers. Examples of specs include American Beauty, Basic Instinct, Bruce Almighty, Hangover and The Truman Show. The Feb 2, 1999 issue of *Variety*, an industry trade magazine, reported that among 146 movies released by major studios in 1998, 12% originated from pitches, and 43% from specs. The rest were based on books, plays, sequels, etc.

[5]Here, a project typically takes about three years from conception to theatrical release. In contrast, in the pharmaceutical industry, it takes a decade or longer for a therapeutic product to move from animal studies to approval (Lerner and Merges (1998)).

[6]Goetzmann et al. (2012) use similar data but focus only on specs. They study the pricing of intellectual property when there exists soft information.

is the lowest for writers with one or two credits. Both the decline and the increase are economically and statistically significant. Other aspects of the data (such as price and the likelihood of release) confirm that this particular measure is reasonably good, and this non-monotonic pattern is also robust to alternative ways of measuring the writer's observable quality.

Other predictions of the model are also borne out by the data. Many studies in the literature have predicted the seller's selection behavior (e.g., Hellmann and Perotti (2011); Allain et al. (2012); Chatterjee and Rossi-Hansberg (2012)). But it has been difficult to test, partly because quality measures are not readily available, and partly because some factors may confound positive findings, while others may countervail the selection effect so that the net quality difference is hard to detect in the data (e.g., Pisano (1997); Arora et al. (2009)). To look for evidence of selection, the model suggests exploiting the heterogeneity in the seller's observable quality. In particular, the model predicts that, conditional on release, the expected performance of a spec increases faster with the writers' observable quality than does that of a pitch. The data show a pattern consistent with this prediction for multiple measures of performance, including box office revenues and the gross return on investment.

Many argue that one of the critical roles played by the IP system is to facilitate the market for ideas—in particular because stronger IP protection allows innovators to explore contracting options without fear of expropriation (e.g., Hellmann (2007a); Elfenbein (2007); Gans et al. (2008)). My results caution against the extrapolation of such arguments to environments in which ideas are abstract, in which it is intrinsically difficult to determine the unauthorized use of the disclosed knowledge from independent creation, and in which the potential of the idea is highly uncertain. An implication of the model is that, in these environments, strengthening legal (especially contract-law) protection of ideas may dampen the buyer's participation incentives. This is especially undesirable for the small and independent sellers that these laws are intended to empower. Many contexts governed by copyright and trade secrets, ranging from advertising and production-promotion ideas to entrepreneurial ideas for a business start-up, share these features.

The model suggests important roles for organizations and institutions that help reduce information asymmetry and the buyer's participation costs. Previous studies have found evidence that venture capitalists help to connect portfolio companies with a network of established firms (Hsu (2004); Robinson and Stuart (2007)). Empirical results here also confirm that for inexperienced sellers, intermediaries are most helpful in lowering the access barriers to the buyer and facilitating earlier-stage sales. However, this paper also provides a subtle view of the effects of intermediaries for experienced sellers. For these sellers, intermediaries are likely to be most helpful in further strengthening the seller's ability to appropriate value. This encourages later-stage transactions, which may actually hurt efficiency.

It is important to recognize that this paper interprets the empirical observations through the lens of a

particular model, which, I believe, is a major driving force of the data. The data and institutional knowledge help to rule out a number of alternative explanations, but not all (e.g., in addition to obtaining a stronger protection, there may be competing reasons to sell later). It is also important to note that, despite seemingly similar sequential development processes, the model may not apply as well to industries protected by strong patents (e.g., the pharmaceutical industry). There, the underlying intellectual property is usually well-defined and well -protected from an early stage. Compared to the expected value of the project, the participation costs the buyer needs to incur are likely to be negligible.

This paper builds upon an extensive literature on the management of innovation in economics and strategy—studying arms-length contracting vs. integration (e.g., Aghion and Tirole (1994)); the structure of optimal licensing contracts (e.g., Gallini and Winter (1985); Katz and Shapiro (1986); Kamien and Tauman (1986)); and the impact of the appropriability environment and the nature of the technologies on the management of innovation relationships (e.g., Teece (1986); Pisano (1991); Gans et al. (2002)).[7] This paper contributes to this literature by focusing on the timing of the transfer of novel ideas in markets in which property rights are difficult to enforce. I show, both theoretically and empirically, that the seller's decision to further develop an idea and the buyer's decision to participate in the market are intimately related, and they are affected by information asymmetry, appropriability conditions and reputational factors.

A number of papers have also studied the timing of sales (See Allain et al. (2012) for the impact of downstream market structure on the stage of licensing in the biotech industry; Jensen et al. (2003) on the faculty's choice of disclosing their inventions at the proof-of-concept versus the prototype stage and its effects on the terms of licensing; and Gans et al. (2008) on how resolving uncertainties over the scope of IP rights affects the contractual terms. Complementing these studies of technology markets, this paper provides some fresh evidence on a market for creative ideas. The paper also goes a step further to examine the outcome data, thus allowing inferences about the quality of the ideas associated with different stages of sales.

Finally, the paper also contributes to the study of the organization of production in creative industries (e.g., Caves (2000); Gil and Spiller (2007)). There have been numerous studies on various aspects of the movie industry, most of which use data on movies that have been released.[8] This paper provides new evidence on the supply of creative ideas at the early stage of the production process.

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[7] For a useful overview of this literature, please see Arora et al. (2001).

[8] For example, on estimating demand (Einav (2007)), the choice of financing (Goettler and Leslie (2004)), strategic choice over release dates (Corts (2001)), and firm boundaries and contracts (Weinstein (1998); Natividad (2013)).

2 Theory

A writer, W, has a nascent idea that he wants to sell to a buyer, B. Both players are risk-neutral. The idea's ultimate value, V, is the sum of four parts:

$$V = w + \theta + \varepsilon_i + \varepsilon_s.$$

w represents the writer's observable quality, which helps the buyer to assess the idea's average value before learning about its specifics. θ measures how much this particular idea's value deviates from the average. ε_i and ε_s are, respectively, the uncertain quality of the idea and of the script; and the realization of these uncertainties happens after the buyer's evaluation. The buyer could provide valuable information on an idea's demand because of her extensive experience in producing and marketing movies, or because of her idiosyncratic demand that is unknown to the writer. For simplicity, assume that all random variables have a mean of zero; the support of all variables is $\mathbb{R}$; and they are independent of each other.

At the beginning of the game, w and the distributions of the random variables are common knowledge, and the writer privately observes θ. The game proceeds as follows:

Stage 1. Given w and θ, the writer decides to spec, to pitch, or to drop the idea. If spec, the writer pays the writing cost, c_s; if pitch, the writer pays no costs; and if drop, the game ends.

Stage 2. Given w and the writer's choice, the buyer decides whether to meet the writer. If they meet, the buyer pays a meeting cost, c_m; otherwise, the game ends. The meeting cost includes the actual and opportunity costs of evaluating an idea's potential, as well as the potential legal risk from the exposure to an idea.

Stage 3. Given a meeting, the storyline is disclosed if a pitch, and the script is disclosed if a spec. The buyer now also observes θ. In addition, ε_i is realized for a pitch, and both ε_i and ε_s are realized for a spec. Both players observe the realized values.

Stage 4. The idea is dropped if its expected surplus is negative. Given positive surplus, the writer makes a take-it-or-leave-it offer.[9] For a spec, the buyer transfers an amount to the writer in exchange for the script. For a pitch, the buyer pays the writer; the writer pays the writing cost; and, given realized ε_s, the buyer decides whether or not to continue the project.

The writer makes the offer under the shadow of buyer expropriation. For example, the buyer may pass on the content to another writer and commission a script. Assume that the buyer's expected payoff from expropriation is $(1 - \lambda_s)$ (resp. $(1 - \lambda_p)$) proportion of the spec's (resp. pitch's) expected surplus, where

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[9]The qualitative results do not change when allowing both players to have some bargaining power—e.g., with a generalized Nash bargaining solution where the writer's bargaining power is an arbitrary number between 0 and 1.

λ_s and λ_p are the writer's ability to appropriate rent (e.g., the likelihood of successful enforcement). More importantly,

Assumption 1. $\lambda_s > \lambda_p$.

First, an obvious motivation for this assumption is that copyright protection is more effective when there is a complete script. Copyright does not protect abstract ideas, but protects is the particular way the ideas are expressed in written works. Even though many writers prepare a treatment (a written account of the storyline, often no more than a couple of pages) when they pitch, the plots, dialogues, and characters in a complete script are much more concrete than those in a treatment. Therefore, the probability of winning an infringement suit is generally greater with a complete script. Second, Anton and Yao (1994) argue that the threat of selling the idea to a rival buyer (thus, undermining the current buyer's monopoly position) allows the seller to capture positive rent. Applying this intuition, a spec imposes a greater threat than a pitch does because a rival buyer can bring a spec to the next stage—and eventually to the market—much faster.[10] Third, stronger IP protection may also generate greater revenue because it allows for a different sale mechanism. For example, selling through an auction is easier when the seller is less concerned with expropriation; and auctions, in general, yield greater revenues to the seller than bilateral negotiations do (Gans and Stern (2010)).[11]

The following assumption on relative costs simplifies the analysis and is broadly consistent with the reality of the movie industry. Relatively speaking, for a spec, the writer's upfront cost (i.e., the writing cost) is greater than the buyer's upfront cost (i.e., the meeting cost); that is,

Assumption 2. $\dfrac{c_s}{\lambda_s} > \dfrac{c_m}{1-\lambda_s}$.

Technically, the assumption bounds from above the writer's share of the idea's surplus, λ_s, with respect to other parameters. It helps rule out a scenario that is not supported by the data.

Lastly, assume that the random variables have the following standard properties.[12]

Assumption 3. *The probability distributions of* θ, ε_i, ε_s, *and* $\varepsilon_i + \varepsilon_s$ *have 1) a monotone increasing hazard rate (e.g.,* $\frac{g(\theta)}{1-G(\theta)}$ *increases with* θ*), and 2) a monotone decreasing reversed hazard rate (e.g.,* $\frac{g(\theta)}{G(\theta)}$ *decreases with* θ*).*

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[10]This argument is intuitively similar to "lead time," which is found to be the most effective appropriation mechanism in many industries (Levin et al. (1988); Cohen et al. (2000)).

[11]In the scriptwriting context, however, different sale mechanisms do not seem to be an important factor. The data show that only 4% of the sales are through auction, and the percentage is not significantly different between specs and pitches.

[12]Log-concave distributions have such properties (see Bagnoli and Bergstrom (2005) for a list of examples).

2.1 Equilibrium

I solve the game for a semi-separating perfect Bayesian equilibrium.[13] By backward induction, I start with stage 4, from which the equilibrium payoffs enter the writer's and the buyer's problems.

A. Equilibrium payoffs at stage 4

Because all uncertainties are realized for a spec, sale takes place if and only if $V \geq 0$. The writer's and the buyer's payoffs are, respectively, $\lambda_s V$ and $(1 - \lambda_s)V$. Recall that the buyer's expected payoff from expropriation is $(1 - \lambda_s)V$, which is what the buyer gets when the writer has all the bargaining power.

Given a pitch, only ε_i is realized. Because the buyer has a chance to terminate the project once the script is finished (i.e., after ε_s is realized), the expected value of a pitch is

$$v(w, \theta, \varepsilon_i) = \mathbb{P}(V \geq 0)\mathbb{E}_{\varepsilon_s}[V|V \geq 0]. \tag{1}$$

A pitch is sold if and only if it is worth writing; i.e., $v(w, \theta, \varepsilon_i) \geq c_s$. Under the threat of buyer expropriation, the writer's and the buyer's equilibrium payoffs are $\lambda_p(v(w, \theta, \varepsilon_i) - c_s)$ and $(1 - \lambda_p)(v(w, \theta, \varepsilon_i) - c_s)$.

B. Writer's problem at stage 1

Given w and θ, the writer anticipates whether or not the buyer will meet him at stage 2 and decides to spec, to pitch, or to drop the idea accordingly. Assume that the writer drops the idea if he anticipates not being met. The writer's expected payoff from a spec (conditional on being met) is the probability that a spec is sold, multiplied by his expected payoff conditional on sale and minus the writing cost; that is,

$$S^W(w, \theta) = \mathbb{P}(V \geq 0)\mathbb{E}_{\varepsilon_i, \varepsilon_s}[\lambda_s V|V \geq 0] - c_s.$$

His expected payoff from a pitch (conditional on being met) is similarly defined, except that the writer incurs the writing cost only if the pitch is sold.

$$P^W(w, \theta) = \mathbb{P}(v(w, \theta, \varepsilon_i) \geq c_s)\mathbb{E}_{\varepsilon_i}[\lambda_p(v(w, \theta, \varepsilon_i) - c_s)|v(w, \theta, \varepsilon_i) \geq c_s].$$

C. Buyer's problem at stage 2

Observing w and the writer's choice of the sale stage, the buyer decides whether to meet the writer. She updates her belief about θ according to the writer's strategy and Bayes' rule. Let $h(\theta|w, S)$ be the buyer's

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[13]Pooling equilibria also exist. However, they can be eliminated by the intuitive criteria (Cho and Kreps (1987)). I also focus on separating equilibrium here because, in the data, I observe both specs and pitches for each value of the (measured) observable quality of the writer, and the proportion of each seems too substantial to be caused by noise.

posterior of θ seeing a writer of w with a spec, and $h(\theta|w,P)$ be that for a pitch. The buyer's expected payoffs from meeting a spec and a pitch are

$$S^B(w) = \int \{\mathbb{P}(V \geq 0)\mathbb{E}_{\varepsilon_i,\varepsilon_s}[(1-\lambda_s)V|V \geq 0] - c_m\} h(\theta|w,S)d\theta,$$

$$P^B(w) = \int \{\mathbb{P}(v(w,\theta,\varepsilon_i) \geq c_s)\mathbb{E}_{\varepsilon_i}[(1-\lambda_p)(v(w,\theta,\varepsilon_i)-c_s)|v(w,\theta,\varepsilon_i) \geq c_s] - c_m\} h(\theta|w,P)d\theta.$$

D. Equilibrium

The following proposition describes the players' equilibrium strategies.[14] The equilibrium is unique because the players' payoffs are monotonic given the other's strategy and Bayes' rule.

Proposition 1. *There exists a unique semi-separating equilibrium, in which the buyer always meets the writer for a spec and meets the writer for a pitch if and only if $w \geq \bar{w}$. The writer's strategy is such that:*

(i) when $w \geq \bar{w}$, he specs if $\theta \geq r_0(w)$ and pitches otherwise;

(ii) when $w < \bar{w}$, he specs if $\theta \geq r_s(w)$ and drops the idea otherwise.

Furthermore, $r_0'(w) = r_s'(w) = -1$.

Figure 1: Writer's Choice in Equilibrium
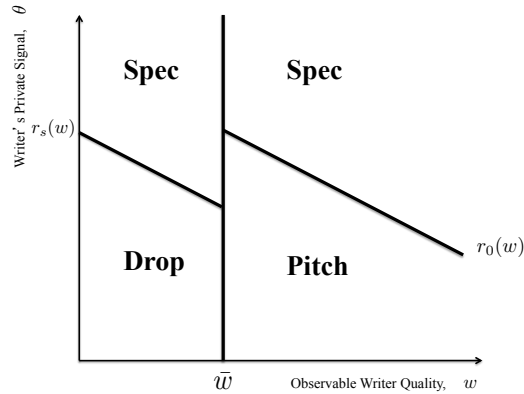
Notes: $\bar{w}$ is the buyer's meeting threshold for pitches. When $w < \bar{w}$, the writer is indifferent between speccing and dropping the idea when $\theta = r_s(w)$; and when $w \geq \bar{w}$, the writer is indifferent between speccing and pitching the idea when $\theta = r_0(w)$.

Figure 1 illustrates the writer's choice in equilibrium. There are three notable features. First, when $w \geq \bar{w}$, the writer selects better ideas to spec and worse ideas to pitch. To see this, write the writer's payoff

[14]The proofs of Proposition 1 and all hypotheses are available in the Online Appendix on the author's website.

difference between speccing and pitching, $\Delta^W(w,\theta) = S^W(w,\theta) - P^W(w,\theta)$, as follows:[15]

$$\begin{aligned}
\Delta^W(w,\theta) &= \lambda_p \mathbb{P}(v(w,\theta,\varepsilon_i) < c_s) \mathbb{E}_{\varepsilon_i}[v(w,\theta,\varepsilon_i) - c_s | v(w,\theta,\varepsilon_i) < c_s] \\
&\quad -(1-\lambda_p)c_s + (\lambda_s - \lambda_p)\mathbb{E}_{\varepsilon_i}[v(w,\theta,\varepsilon_i)].
\end{aligned} \tag{2}$$

Pitching is desirable for two reasons. One is the informational value of the buyer's feedback, so that if the idea turns out not to be that interesting, the writer can save himself the writing cost. $\lambda_p \mathbb{P}(v(w,\theta,\varepsilon_i) < c_s)\mathbb{E}[v(w,\theta,\varepsilon_i) - c_s | v(w,\theta,\varepsilon_i) < c_s]$ is the writer's share of the improved efficiency relative to a spec. Pitching is also desirable because the writer has not yet sunk the writing cost, which is reflected by $-(1-\lambda_p)c_s$. However, speccing is desirable because the writer obtains a greater share of the idea's surplus (due to a smaller risk of expropriation). This appropriation advantage of speccing is reflected by $(\lambda_s - \lambda_p)\mathbb{E}[v(w,\theta,\varepsilon_i)]$.

For any $w \geq \bar{w}$, the writer follows a threshold strategy because speccing becomes more attractive as θ increases (i.e., $\Delta^W(w,\theta)$ is monotone increasing in θ). In particular, bigger θ means a better expected value of the idea, which implies a bigger incentive to capture a greater share of the surplus and less of a need for interim feedback from the buyer.

Second, $r_0(w)$ decreases with w, implying that writers with better w spec more often. This is because w and θ both contribute positively to the idea's expected value. Therefore, ideas from writers with better w need to have lower θ to be above the threshold.

Third, the buyer also follows a threshold strategy in meeting the writer, but, more interestingly, she is stricter about meeting a pitch than a spec. As a result, when $w < \bar{w}$, the writer either has to develop a full script or drop the idea entirely. To see this, consider the marginal writer, $\bar{w}$, who the buyer is indifferent about meeting for a pitch. However, the buyer may still want to meet him for a spec because: 1) a spec signals a better posterior distribution of θ; and 2) the writer has already sunk the writing cost. But on the flip side, the buyer is able to appropriate less when the writer sells a spec (i.e., $1 - \lambda_s < 1 - \lambda_p$). Therefore, the buyer is still happy to meet $\bar{w}$ for a spec as long as she does not need to give up too much more of the surplus (i.e., λ_s is not too much higher than λ_p). Assumption 2 implies that $\lambda_s < \frac{c_s}{c_m + c_s}$ and is a sufficient condition to guarantee that this is the case.

2.1.1 Discussion of the Model's Assumptions

A number of assumptions in the model simplify the analysis, but some are not without loss of generality. Below, I briefly discuss conditions under which Proposition 1 holds qualitatively when these assumptions are relaxed. First, the idea's ultimate value V does not need to be linear, and the elements also do not need

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[15]Notice that $\mathbb{P}(V \geq 0)\mathbb{E}_{\varepsilon_i,\varepsilon_s}[V|V \geq 0] = \mathbb{E}_{\varepsilon_i}[v(w,\theta,\varepsilon_i)]$.

to be independent of each other. It is sufficient that V is an increasing function of all its elements, and approaches ∞ (resp. $-\infty$) as we take each element to ∞ (resp. $-\infty$). In fact, the assumptions on limits are not necessary either, but they guarantee the existence of the solution without having to specify boundary conditions of the parameter values.

Second, the writing cost can vary across writers. Intuitively, more-experienced writers have a lower writing cost (i.e., $\frac{\partial c_s(w,\theta)}{\partial \theta} \leq 0$). Proposition 1 holds if this is true because, relative to the baseline case, as w increases, speccing is even more attractive because the upfront investment is now also lower. Even in the scenario in which $\frac{\partial c_s(w,\theta)}{\partial \theta} > 0$, as long as the rate of increase is sufficiently slow, the equilibrium results should still hold.

Third, the ability to protect one's idea may increase with w (i.e., $\frac{\partial \lambda_s(w)}{\partial w} > 0$ and $\frac{\partial \lambda_p(w)}{\partial w} > 0$). Given any w, it is intuitive that a complete script is still better protected; hence, the writer still favors speccing better ideas and pitching worse ones. The overall equilibrium results hold if 1) the rates of increase of the $\lambda(w)$'s w.r.t. w are not too high because, otherwise, the buyer may not want to meet better writers, as she would give up too great a share of the surplus; and 2) $\frac{\partial(\lambda_s(w)-\lambda_p(w))}{\partial w}$ is not too negative because, otherwise, top writers may not find it more attractive to spec than intermediate writers.

Fourth, the variance of ε_i and ε_s can also vary with w, and, intuitively, it decreases with the writer's experience. Because the option to reject the idea (or terminate the project) when the realized value is too low removes the downside risk, higher variance implies a higher expected value. Then, w has two opposite effects on an idea's expected value: on the one hand, higher w increases an idea's value directly; on the other hand, higher w is associated with a lower variance of ε_s and ε_i and, thus, lowers the idea's expected value. As long as the variance of ε_s and ε_i does not decrease with w too fast, the positive direct effect dominates, and Proposition 1 holds qualitatively.

2.2 Empirical Implications

Figure 1 immediately implies that conditional on sale, the likelihood of a spec is non-monotonic with respect to the writer's observable quality. When $w < \bar{w}$, the likelihood of a spec is one because the buyer would not meet the writer for pitches. Once the writer is good enough to get his pitches heard, the likelihood of a spec drops. However, as w increases, it is in the writer's own interest to spec more often. Thus,

Hypothesis 1. *Conditional on sale, the likelihood of a spec is high for writers of both low and high observable qualities, and low for writers in the middle.*

Another implication that is immediate from Figure 1 is that, given w, the quality of ideas offered for sale as a spec is higher than that of a pitch. The availability of performance data in the movie industry

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provides potential opportunities to test for the seller's selection behavior, which is also predicted in other models studying idea sales or spin-offs (e.g., Hellmann and Perotti (2011); Allain et al. (2012); Chatterjee and Rossi-Hansberg (2012)).

Previous studies have used price or the likelihood of success to infer a project's quality. Here, neither is quite appropriate to test for seller selection. First, comparing the release likelihoods between specs and pitches is problematic because, even without selection, specs should be more likely to succeed simply because there is less uncertainty. To isolate the difference in uncertainty, we want to compare specs to the set of pitches that are continued to the next stage after the first drafts are written. Unfortunately, we do not observe this intermediate step. Second, it is hard to conclude that selection exists even if specs are priced higher than pitches because the price of specs is conditional on additional information of ε_s being sufficiently high and because price reflects the writer's share of the surplus, and the share is higher with a spec.

Here, I propose comparing the movie's performance conditional on release because released movies have comparable degrees of uncertainty, and the revenue reflects the total size of the pie. For simplicity, assume that the realization of ε_s is the last stage before release.[16] Given w, the expected performance of a spec conditional on release is $\mathbb{E}_{\theta,\varepsilon_i,\varepsilon_s}[V|\theta \geq r_0(w), V \geq 0]$, and that for a pitch is $\mathbb{E}_{\theta,\varepsilon_i,\varepsilon_s}[V|\theta < r_0(w), v(w,\theta,\varepsilon_i) \geq c_s, V \geq 0]$. These expressions show that the performance difference comes from the initial sourcing stages: On the one hand, the "writer-selection effect" makes specs better, on average, because the distribution of θ of a spec is better than that of a pitch; on the other hand, the buyer screens pitches for an extra round (that is, pitches are purchased only if ε_i is sufficiently high such that $v(w,\theta,\varepsilon_i) \geq c_s$), and this "extra-screening effect" makes pitches, on average, better.

The extra-screening effect may countervail the selection effect and make it hard to detect any quality difference (Arora et al. (2009) make this argument informally when finding no evidence for selection in the pharmaceutical industry). Interestingly, the relative importance of these two effects varies with w. In particular, the extra-screening effect is the biggest for low w and diminishes as w gets better because pitches from top writers are most likely to be taken anyway. In contrast, the writer-selection effect is the biggest for writers of high w. This is because the expected value of pitches is bounded from above by a threshold; and, as a result, even though the expected performance for both specs and pitches increase with w, the former is theoretically unbounded, while the latter is not. Combining the above two effects, we have the following:

Hypothesis 2. *Conditional on release, the movie's expected performance increases with w for both specs and pitches, with the former increasing faster than the latter.*

Recall that w can take any value in R in the model. Theoretically, we should observe that the expected

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[16]It is straightforward to extend the model to include uncertainty shocks and development costs for later stages, and the arguments are similar.

performance of specs and pitches crosses: Pitches perform better than specs for the lowest values of *w* because of the extra-screening effect; but because of a faster rate of increase, specs eventually perform better for the highest values of *w*. Empirically, however, we may not observe this pattern because the data may capture only a partial range of *R*; that is, depending on the range captured, it is also possible that specs always perform better or pitches always perform better. What we should not observe, however, is specs performing better than pitches for writers with low *w*, but worse than pitches for writers with high *w*.

3   Data

The primary data source for this paper is *Done Deal Pro*, an internet database that has tracked transactions of movie ideas in Hollywood since 1997.[17] It covers a significant portion of projects at major studios and big production companies; for example, a manual check of movies distributed by the major studios in 2008 reveals that about 70% of them are in the sales database. The sales data are matched to *IMDb*, which has comprehensive information on a person's resume in the industry, and to *TheNumbers*, which has performance data for released movies.

Because this paper studies original-idea sales by writers, the following cases are excluded: 1) transactions of movie rights for literary materials (e.g., a book); 2) commissions from the buyer to adapt material or other people's ideas into scripts or to rewrite an existing script; 3) authors adapting their own work (e.g., a novel) into a script; and 4) specs or pitches that are based on existing materials. These cases, together, account for 55% of the projects pursued by the studios. I use ideas sold by 2005 to leave enough time to observe the final outcome of a sale by 2009. Finally, not all sales indicate whether they are specs or pitches. Using two complementary sources, *Hollywood Literary Sales* and *Who's Buying What*, I complete this information for about 70% of the sales. Thus, the final sample for analysis contains 1,834 sales.

A number of limitations of the data constrain the empirical tests. First, ideas that are rejected are not observed and, hence, cannot test the writer's choice directly. Such data are hard to find, in general. I compensate by deriving predictions that are conditional on sale. Second, because I do not observe which pitches are terminated after the first draft, I cannot use the likelihood of release to compare the quality of specs and pitches. An advantage of having a model is to guide the exploration of the data; here, the model implies using the performance of released movies to test the quality difference. Third, the number of observations at the higher end of the writer's observable quality is small, which is also typical for such studies. Therefore, certain parametric specifications are necessary for some tests.

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[17]The database is obtained from www.donedealpro.com. It is recommended by various industry organizations, including the Writers Guild of America, as a valuable resource to stay up-to-date on projects developed.

Finally, it is important to note that survival bias (i.e., the writers in the sample have not exited the industry) is not a concern in this paper because its target audience is actually the survived sample. The writer decides when to sell a particular idea after he has decided to stay in the market. The buyer, when deciding whether to meet a writer or whether to buy the idea, also, naturally, faces a writer who has already decided to stay in the market.

3.1 Empirical Specifications

The empirical method is straightforward: to look at relationships between variables in the data and determine whether they are consistent with the model's predictions. The unit of analysis is a sale. The analysis is cross-sectional because 80% of the writers have only one sale. In all regressions, however, the standard errors are clustered at the writer level.

To test Hypothesis 1, the following probit model regresses SPEC on a group of dummy variables indicating each value of WEXP, where SPEC indicates that a sale is a spec and WEXP is a discrete measure of the writer's observable quality.

$$\mathbb{P}(\text{SPEC}_i = 1) \quad = \quad \mathbb{P}(\beta_0 + \sum_{k=1}^{K} \beta_k 1_{\{\text{WEXP}_i = k\}} + \beta_X X_i + u_i \geq 0), \tag{3}$$

where X_i are controls, including the writer's non-scriptwriting experience and characteristics of the idea; and u_i captures unobservable factors that might also affect the idea's sale stage. The objective is to see whether the expected likelihood of a spec sale first decreases and then increases as the value of WEXP increases.

To test Hypothesis 2, I use the following specification for movies that are eventually released. Because the number of observations is limited at the higher end of WEXP, a linear model with an interaction term (instead of dummies indicating the sale stage for each value of WEXP) is used.

$$\text{Performance}_i \quad = \quad \beta_0 + \beta_1 \text{SPEC}_i + \beta_2 \text{WEXP}_i + \beta_3 \text{SPEC}_i \cdot \text{WEXP}_i + \beta_M M_i + v_i, \tag{4}$$

where performance is measured by a movie's box office revenues or its gross return on investment; and M_i are controls that might affect performance. Here, the objective is to see whether the expected performance of a spec increases faster than that of a pitch (that is, $\beta_3 > 0$).

It is important to clarify that there is no correction for the selection bias of selling on spec or the survival bias of reaching the release stage in regression (4) because the goal of the empirical tests is to see whether the data are consistent with the predicted equilibrium relationships. In other words, because the paper is not seeking to estimate the causal effects of the sale stage on a movie's performance, it is not necessary to apply

the usual methods for causal inference.

3.2   Variables

Table 1 provides the descriptive statistics for the variables.

WEXP is the main measure of the writer's observable quality; it is defined as the number of writing credits the writer has obtained in the previous five years for movies that are produced or distributed by a major studio (hereafter, major writing credits).[18] The restriction to the previous five years captures the writer's current status and avoids simply measuring his tenure in the industry. Restricting to major studios avoids inflating the number with small-budget independent movies. Whenever there are more than one writer, the maximum of the writers' credits is taken as that of the team. 79% of the sales are from writers with zero credits, and for the other 21%, the average is 1.52.[19] Later, for robustness, I use alternative measures that also include the writer's complete history and independently produced movies.

Note that for each value of WEXP, writers who have been tested over an extended period and newer writers are pooled, and the lower the experience level, the greater the proportion of newer writers. It is reasonable to assume that the mean quality of new writers is lower than that of writers with more credits because only better writers stay in the market. Thus, this complication from mixing writers with different entry times is actually consistent with the purpose of the measure: a higher experience level implies a better-quality writer.

Overall, 54% of the sales are specs. Table 2 shows that 59% of the sales from writers with zero credits are specs. The proportion drops to 36% for writers with one or two credits (the drop is statistically different from zero at the 1% level). For writers with three or four credits, the proportion increases back up to 46%. The increase in magnitude is quite substantial, and statistically significant at the 10% level with a one-sided test. The raw data provide preliminary evidence that support the predicted non-monotonic relationship between the likelihood of a spec sale and the writer's observable quality.

A movie is defined as released if it is theatrically released in the U.S. and has positive box office revenue.[20] Overall, 12% of the sales are released. Table 2 shows that the release likelihood is significantly higher for specs for all values of WEXP, which is not surprising given that there is less uncertainty.

Box office revenues are available for released movies. Table 2 shows a pattern that is consistent with

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[18]The following ten studios and their divisions are included: Walt Disney, Warner Bros., Paramount, Universal, Fox, Sony Pictures Entertainment, DreamWorks SKG, New Line Cinema, MGM, and Miramax Films.

[19]The raw measure ranges from zero to seven. I group writers with more than four credits at four to obtain a decent number of observations for the top cell.

[20]Because specs are more developed, the release time for a spec is cut by July 2009 and that for a pitch by November 2009. The four-month difference is because a typical pitch contract gives the writer three months to finish the first draft and the buyer two weeks to a month to decide whether to continue. There are six cases in which the movies were released at film festivals, and the box office revenues are recorded as $0. I categorize them as not released.

Table 1: Descriptive Statistics for Selected Variables

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
SPEC	Dummy, 1 if sale is a spec	1,834	0.54	0.50	0	1
WEXP	Number of writer's major writing credits in the previous five years	1,834	0.33	0.73	0	4
BIGAGENT	Dummy, 1 if writer is affiliated with one of the five biggest agencies	1,834	0.40	0.49	0	1
WRITER_TENURE	Number of years since writer's first writing credit	1,834	6.02	8.46	0	60
WRITER_TV	Dummy, 1 if writer has any major TV writing credit	1,834	0.05	0.23	0	1
WRITER_DIRECTOR	Dummy, 1 if writer has any major directing credit	1,834	0.07	0.25	0	1
WRITER_ACTOR	Dummy, 1 if writer has any major acting credit	1,834	0.15	0.36	0	1
WRITER_PRODUCER	Dummy, 1 if writer has any major producing credit	1,834	0.14	0.35	0	1
NUM_WRITER	Number of writers in the team	1,834	1.35	0.51	1	3
ATTACH_STAR	Dummy, 1 if there are stars attached	1,834	0.20	0.40	0	1
ATTACH_DIRECTOR	Dummy, 1 if there is a director attached	1,834	0.13	0.33	0	1
RELEASE	Dummy, 1 if the movie is released in theater	1,834	0.12	0.32	0	1
PRICE	Price of two drafts and a polish ($000)	1,010	319.20	345.57	1	5000
US_BO	U.S. box office revenue in $million	217	45.66	47.72	0.00	242.71
WORLD_BO	Worldwide box office revenue in $million	176	95.27	108.62	0.30	624.35
GROSS_RETURN	U.S. box office/production budget	191	1.57	1.44	0.02	8.67
PROD_BUDGET	Estimated production budget in $million	191	36.83	26.05	1.5	150
NUM_SCREEN	# screens during 1st weekend of the movie's release	217	2181.14	1054.62	1	3965
NUM_STAR	Dummy, 1 if there are highly-paid stars	217	0.20	0.40	0	1
DIRECTOR_EXP	Number of directing credits of the movie's director	217	4.37	5.15	0	21

Notes: The unit of analysis is a sale. Whenever there are more than one writer, I take the maximum of the writers' experience as that of the team. Descriptive statistics of dummies for genre, buying studio, creative type, MPAA rating, sale year, release year, and release week are omitted.

Table 2: Descriptive Statistics for Main Variables

		WEXP = 0		WEXP = 1 or 2		WEXP= 3 or 4	
		N	Mean	N	Mean	N	Mean
SPEC		1,443	0.59***	343	0.36*	48	0.46
RELEASE	SPEC = 1	850	0.13***	122	0.20**	26	0.64***
	SPEC = 0	593	0.07	221	0.11	22	0.19
log(USGROSS)	SPEC = 1	109	2.79	25	3.05	14	4.12*
	SPEC = 0	42	3.11	25	3.44	5	3.57
log(PRICE)	SPEC = 1	464	5.28***	66	5.79	17	6.75**
	SPEC = 0	362	5.44	123	5.75	14	5.97

Notes: The number of observations for WEXP = 0 to 4 are, respectively, 1443, 242, 101, 33, and 15. The significance levels indicate the results from one-sided tests. For SPEC, the tests are between a particular WEXP group and the next one. For RELEASE, log(USGROSS) and log(PRICE), the tests are between spec sales and pitch sales. ***, **, and * are, respectively, significant at levels of 1%, 5%, and 10%.

Hypothesis 2: The U.S. box office revenues of specs have a higher rate of increase with WEXP than those of pitches. In particular, for WEXP less than or equal to two, specs and pitches perform similarly, while for WEXP greater than two, specs perform better (significant at the 10% level with a one-sided test). The regressions also use the worldwide box office revenues and gross return on investment (the ratio between

U.S. box office revenues and the production budget) as alternative measures for movie performance.

I observe price data for only 56% of the sales. Typically, for both specs and pitches, the reported price consists of two parts: "front-end payment," which is roughly the price for two drafts and a polish; and "credit bonus," which is paid only if the movie is produced.[21] Even though the overall quality is not great,[22] price data still provide useful information on the evaluation of an idea. PRICE is defined as the amount of the front-end payment. Table 2 shows a pattern similar to that of the U.S. box office: The average price increases with WEXP for both specs and pitches; specs are, on average, priced lower than pitches for low values of WEXP, and priced higher for high values of WEXP.

The sets of control variables are defined as follows:

Other writer characteristics. This set of variables includes the writer's tenure (the number of years since the writer's first movie-writing credit); dummies indicating whether he has written for major TV networks, ever obtained a directing, acting (top five listed actors/actresses in a movie, by importance), or producing credit for movies by the major studios. The number of writers in the team is also controlled for.

Intermediary. BIGAGENT indicates the association with one of the five biggest agencies.[23] About 40% of the sales are through these five agencies, and sales from writers with a big agency are more likely to be a pitch than sales from writers without a big agency (59.9% vs. 42.9%).

Buyer. Studio buyers are different from independent production companies in their capacity, resources, and marketing capabilities. I include ten dummies indicating that one of the ten major studios is listed as a buyer. The major studios buy 62.3% of the ideas.

Idea characteristics. Ten dummies for genre are included because, in addition to capturing market size and competition, the writing of an idea is said to be more critical for some genres (e.g., comedy) than for others (e.g., action). Agents sometimes attach talents to a project to attract buyers, which is called packaging. Two dummies indicating whether there are stars or a director attached at the time of the sale are included.

Characteristics of released movies. This set of variables includes production budget, the number of screens in the first weekend,[24] whether there are highly-paid stars,[25] the director's experience, dummies for genre, MPAA rating, year of release, week of release, and creative type.[26] These variables control for the

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[21]If the original writer(s) share the writing credit with other writing teams, they also share the bonus.

[22]In addition to missing data, many report only the sum of the two parts and often in rough ranges (e.g., high six figures). For the purpose of analysis, I divide the sum by a typical 1:1.5 proportion between the two parts and impute a number considered reasonable by practitioners for rough ranges.

[23]During the time period studied, the big five were Creative Artists Agency, United Talent Agency, William Morris, International Creative Management, and Endeavor. In 2009, Endeavor and William Morris merged.

[24]Prior studies have documented that the number of screens in the opening weekend is highly correlated with the amount of resources allocated to the promotion of a movie (e.g., Sorenson and Waguespack (2006)).

[25]STAR indicates whether the movie is on the list of top 1,000 "Highest Combined Star Gross" defined by *TheNumbers*.

[26]MPAA (Motion Picture Association of America) rating reflects a film's thematic and content suitability for certain audiences. The ratings are G, PG, PG-13, R, and NC-17, in increasing order of inappropriateness for a younger audience. Creative type is a

nature of the movie (e.g., a mainstream movie versus an art-house movie); the studio's marketing strategy (e.g., a wide versus a limited release); the size of the market (e.g., holiday versus non-holiday seasons); and competition conditions from movies outside the sample (e.g., the year and week of release).

4 Estimation Results

Column (1) in Table 3 reports the Probit estimates for the relationship between the likelihood of a spec sale and the writer's observable quality. Figure 2 plots the relationship, keeping the control variables at their sample means. The predicted probability of a spec is 0.58 for writers with zero major credits in the previous five years; it drops to 0.41 and 0.34 for writers with one and two credits; and it increases back to 0.46 and 0.64 for writers with three and four credits. The drop in the likelihood from zero to one/two credits is about 20 percentage points and significant at the 1% level. The likelihood of a spec for writers with four credits is over 30 (resp. 24) percentage points higher than that for writers with two (resp. one) credits, and the difference is different from zero at the 5% (resp. 10%) level. Column (2) uses a quadratic specification of WEXP, which yields results that are qualitatively similar. Here, the statistical significance for the increase in the likelihood of spec sales from two credits to three and four credits is much stronger than the dummy-variable specification because of the help from the functional-form assumption.[27]

Figure 2: Predicted Probability of a Spec Sale
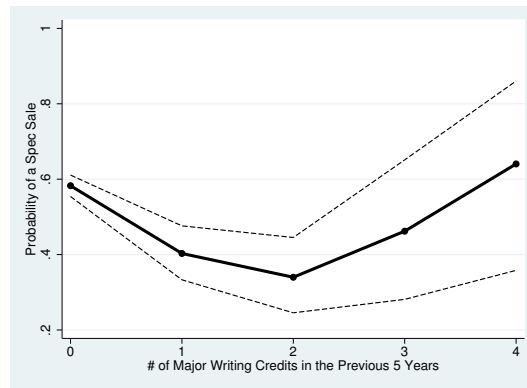
Notes: The dots are predicted probabilities of a spec sale, keeping the control variables at their sample means. The dashed lines are the 95% confidence interval. The plot is based on results in Column (1) of Table 3.

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unique categorization used by *TheNumbers*, including contemporary fiction, kids' fiction, dramatization, factual, fantasy, history fiction, science fiction, and superhero.

[27]In the quadratic specification, the likelihood of a spec sale for writers with three credits is statistically different from that for WEXP = 2 at the 10% level (t = 1.92), and the likelihood for writers with four credits is statistically different from that for one, two and three credits at the 5% level.

Table 3: Probit Estimates for a Spec Sale (DV = SPEC)

	All Sales (1)	All Sales (2)	WEXP = 0 (3)	WEXP > 0 (4)
WEXP = 1	-0.179***			
	(0.040)			
WEXP = 2	-0.241***			
	(0.053)			
WEXP = 3	-0.121			
	(0.099)			
WEXP = 4	0.059			
	(0.144)			
WEXP		-0.252***		-0.235
		(0.046)		(0.154)
WEXP^2		0.068***		0.058*
		(0.016)		(0.035)
BIGAGENT	-0.116***	-0.116***	-0.136***	-0.037
	(0.027)	(0.027)	(0.031)	(0.060)
WRITER_TENURE	-0.001	-0.001	-0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.003)
WRITER_TV	-0.109*	-0.110*	-0.144*	-0.044
	(0.064)	(0.064)	(0.076)	(0.111)
WRITER_DIRECTOR	0.032	0.032	-0.067	0.031
	(0.060)	(0.060)	(0.094)	(0.079)
WRITER_ACTOR	-0.068*	-0.068*	-0.093**	-0.033
	(0.039)	(0.040)	(0.047)	(0.067)
WRITER_PRODUCER	0.048	0.049	-0.001	0.063
	(0.044)	(0.044)	(0.060)	(0.061)
NUM_WRITER	-0.060**	-0.060**	-0.084***	0.035
	(0.026)	(0.026)	(0.028)	(0.055)
ATTACH_DIRECTOR	0.031	0.031	-0.009	0.176***
	(0.033)	(0.033)	(0.037)	(0.065)
ATTACH_STAR	-0.070*	-0.070*	-0.065	-0.140**
	(0.038)	(0.038)	(0.045)	(0.063)
YEAR_SALE dummies	Y	Y	Y	Y
MAJOR_STUDIO dummies	Y	Y	Y	Y
GENRE dummies	Y	Y	Y	Y
Pseudo R^2	0.115	0.115	0.080	0.079
Log likelihood	-1119.21	-1119.28	-462.86	-463.58
N	1,834	1,834	1,443	391

Note: Marginal effects are reported; and standard errors are clustered at the writer level. (1) uses dummies for each value of WEXP; and (2), (3) and (4) use a quadratic specification of WEXP. ***, **, and * are, respectively, significant levels of 1%, 5%, and 10%.

This non-monotonic result is consistent with Hypothesis 1. Unknown writers face difficulties in obtaining the buyer's attention with earlier-stage ideas (thus forced to sell later); once they are good enough, the likelihood of selling earlier increases. It is interesting to note that the likelihood of spec sales goes back up for top writers. These writers are least likely to face constraints of any sorts, and the result is consistent with the theory that it is in their own interest to spec more often as they get better.

Note that writers with zero credits still sell pitches 42% of the time. This number seems at odds with the

discrete result of the model (that is, writers with $w < \bar{w}$ cannot pitch at all). The most probable explanation is that WEXP does not capture all that the buyer observes about the writer prior to the meeting, and some writers are actually good enough to get their pitches heard. For example, 36% of these writers are represented by the top five agencies, and 5% have written for major TV networks. In addition, the buyer is also likely to observe things that are not in the data. For example, some writers might be working on projects currently in development or might have demonstrated good craftsmanship in previous failed projects. Following the baseline results, I discuss in detail these measurement problems and how they may bias the results.

To look further into writers with zero credits, intuitively, variables that are positively correlated with w or indicate a higher reputation or a deeper connection with the buyer should be associated with a higher likelihood of a pitch sale because these factors are helpful in securing a pitch meeting. Confirming this intuition, Column (3) of Table 3 shows that the sale is more likely to be a pitch if the writer is associated with one of the top five agencies, if the writer has written for major TV networks, if there is more than one writer in the team, and if the writer also has a major acting credit. In contrast, Column (4) shows that these variables show no significant relationships with the sale stage for writers with some major experience.

Table 4 reports the OLS results for movies' performance after release (equation (4)). 26 movies lack production-budget information, and their revenues are substantially lower than the rest (the median U.S. box office revenue is \$3.35 vs. \$35 million). Dropping these observations may over-estimate specs' performance if they are more likely to be specs than the rest of the sample. The data confirm that movies with and without the budget information are not significantly different in the sale stage, both for the overall sample and by values of WEXP. Regressions are run that include and exclude these movies, and they produce consistent results.[28]

Across different specifications, a similar pattern emerges (illustrated in Figure 3): The expected performance of a spec is not different from that of a pitch at the beginning, but it increases faster with WEXP and eventually becomes higher. Take Column (1), for example—for writers with one credit or more, specs perform better than pitches by 37, 67, 97 and 127% (all statistically different from zero at the 5% level). Simpler split-sample results (not reported here) also confirm that specs do not perform differently from pitches when WEXP = 0 and significantly better than pitches when WEXP > 0.

The increasing performance difference between specs and pitches is consistent with the theory's prediction on how the writer-selection effect (which makes specs better) and the extra-screening effect (which makes pitches better) play off against each other for different values of WEXP. Even though Hypothesis 2 points to several possibilities that we may see in the data, actually finding that specs perform significantly

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[28]When the production budget is not available, including the number of screens helps to mitigate the missing variable problem because the two variables have a reasonably high positive correlation. Kuppuswamy and Baldwin (2013) report a correlation of 0.66 between log(number of screens) and log(production budget), and the number is lower in my sample, 0.37.

Figure 3: Predicted Movie Performance Conditional on Release
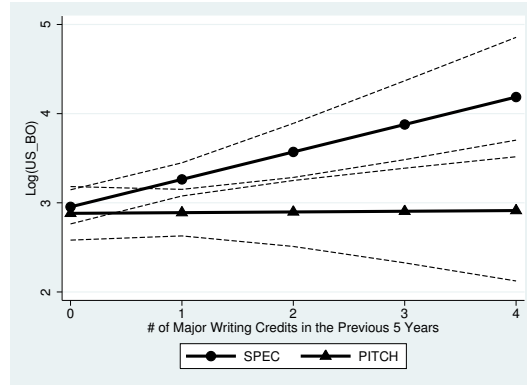
Notes: The dots (triangles) are the predicted log(US_BO) for specs (pitches). The control variables are kept at their sample means. The dashed lines are the 95% confidence intervals. The plot is based on results in Column (1) of Table 4.

Table 4: OLS Estimates for Movie Performance after Release

	(1)	(2)	(3)	(4)	(5)	(6)
	log(US_BO)	log(US_BO)	GROSS_RETURN	GROSS_RETURN	log(WW_BO)	log(WW_BO)
SPEC	0.073	0.036	0.068	-0.044	0.092	0.065
	(0.188)	(0.194)	(0.327)	(0.301)	(0.216)	(0.215)
WEXP	0.008	-0.045	-0.012	-0.100	0.021	-0.047
	(0.115)	(0.141)	(0.188)	(0.176)	(0.135)	(0.148)
SPEC × WEXP	0.300**	0.349**	0.406	0.538**	0.311*	0.384**
	(0.147)	(0.167)	(0.250)	(0.232)	(0.172)	(0.181)
log(PRODBUDGET)		0.582***		-0.880***		0.697***
		(0.147)		(0.218)		(0.151)
log(SCREEN)	0.427***	0.369***	0.268***	0.338***	0.417***	0.360***
	(0.084)	(0.089)	(0.068)	(0.061)	(0.093)	(0.095)
STAR	0.459**	0.227	0.040	0.282	0.613***	0.332
	(0.183)	(0.185)	(0.306)	(0.287)	(0.205)	(0.201)
DIRECTOR_EXP	-0.013	-0.016	-0.018	-0.002	-0.008	-0.011
	(0.017)	(0.015)	(0.024)	(0.023)	(0.019)	(0.016)
MAJOR_STUDIO	0.459***	0.026	-0.245	0.009	0.561***	0.069
	(0.175)	(0.151)	(0.269)	(0.233)	(0.194)	(0.164)
Constant	0.763	-0.375	2.789*	4.986***	1.114	-0.340
	(1.125)	(1.100)	(1.556)	(1.692)	(1.355)	(1.237)
YEAR_RELEASE dummies	Y	Y	Y	Y	Y	Y
WEEK_RELEASE dummies	Y	Y	Y	Y	Y	Y
GENRE dummies	Y	Y	Y	Y	Y	Y
CREATIVE_TYPE dummies	Y	Y	Y	Y	Y	Y
Adj. R^2	0.733	0.603	0.255	0.356	0.712	0.617
N	217	191	191	191	217	191

Note: 26 movies have no production-budget information. US_BO and WW_BO are U.S. and worldwide box office, and GROSS_RETURN is defined as US_BO/PRODBUDGET. The standard errors are clustered at the writer level; and ***, **, and * are significant levels of 1%, 5%, and 10%.

better than pitches for higher values of WEXP provides more convincing evidence for seller selection.

The model explains the relationship between performance and the sale stage through selection: The difference in the average quality of these two types of projects comes from how the writer selects and how the buyer screens the ideas. In fact, interpreting these patterns through the lens of the model implicitly assumes that there is little causal effect. In other words, the difference in the sourcing stage, per se, does not cause different treatments of these projects—e.g., having different screening criteria at later milestones or favorable allocation of resources towards one type versus the other. Section 4.2 discusses potential causal explanations and argues that they are unlikely to explain the patterns observed in the data.

4.1 Measures of the Writer's Observable Quality, w

A. Robustness of the main measure, WEXP.

The measure WEXP is straightforward and relatively stringent, so each incremental increase contains substantial variation. It is also transparent in the sense that the measure comes from the raw data without extra construction. Still, it is unlikely that WEXP captures all that is in w; and the unaccounted-for part may be captured by other observable characteristics of the writer or is unobservable and, hence, falls in the error term. The main concern is that if WEXP is sufficiently negatively correlated with the unaccounted-for part, it may not preserve the rank order of w. Then, it would be problematic to link findings based on WEXP to the model; e.g, writers with three or four credits may appear only to be of high quality, while, in fact, their true w is inferior to that of writers with one or two credits.

Further examination of the data alleviates this concern. First, WEXP is positively correlated with other writer characteristics that are potentially positively correlated with the writer's observable quality.[29] Second, the data are split into subsamples, according to whether the writer also has a major directing, producing, or acting credit and whether the writer is affiliated with a big agency. Each subsample keeps one dimension of the writer's other characteristics constant at a time, and the results (omitted in the interest of space) also exhibit a significant non-monotonic relationship between the likelihood of a spec sale and WEXP. Third, Table 5 shows that for both specs and pitches, the purchasing price increases significantly with WEXP, and so does the likelihood of release. These two variables intuitively measure an idea's quality, and their positive relationships with WEXP further alleviate the concern that WEXP may reverse the rank order of the true w.

It is worthwhile to note that, for both price and the likelihood of release, a pattern similar to that for the movie's performance emerges (Columns (3) and (6) of Table 5). For example, the price of specs starts significantly lower than that of pitches for writers with zero credits, but it increases faster and is eventually

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[29]The correlations between WEXP and WRITER_TENURE, WRITER_TV WRITER_DIRECTOR, WRITER_ACTOR, WRITER_PRODUCER and BIGAGENT range from 0.07 to 0.49 and are all statistically significant.

Table 5: OLS Estimates for Price and Release

	DV = log(PRICE)			DV = RELEASE		
	Specs	Pitches	Both	Specs	Pitches	Both
	(1)	(2)	(3)	(4)	(5)	(6)
WEXP	0.322***	0.131**	0.120**	0.071***	0.028*	0.022
	(0.056)	(0.062)	(0.056)	(0.025)	(0.017)	(0.016)
SPEC			-0.118**			0.066***
			(0.052)			(0.017)
SPEC × WEXP			0.223***			0.057**
			(0.068)			(0.027)
Constant	5.278***	5.350***	5.399***	0.197**	-0.022	0.071
	(0.176)	(0.213)	(0.138)	(0.095)	(0.051)	(0.059)
Controls	Y	Y	Y	Y	Y	Y
Adj R^2	0.285	0.204	0.226	0.131	0.082	0.086
N	547	463	1,010	994	840	1,833

Note: PRICE is roughly the payment for two drafts and a polish. RELEASE is a dummy variable indicating whether the movie is released by 2009. The regressions on RELEASE are linear probability models. All columns use the same controls as in Column (2) of Table 3. Standard errors are clustered at the writer level; and ***, **, and * are, respectively, significant levels of 1%, 5%, and 10%.

higher for top writers. As discussed previously, price data may not serve as clean evidence of the quality difference between ideas offered at different stages because of a number of confounding factors. It is, nonetheless, comforting to find that the data, at least, do not reject the theory's prediction of how prices may compare between sale stages.

B. Alternative measures.

For robustness, two alternative sets of measures of the writer's observable quality are constructed. The first set expands the credits to include the writer's entire writing history and movies by minor studios. Here, a credit is weighted by the corresponding movie's performance. This helps to mitigate potential inflation resulting from including low-budget movies and, to a certain extent, genre heterogeneity (e.g., comedies tend to take less time to produce but also generate lower revenues than action movies). In particular, if a movie's revenue falls in the 90*th* percentile among all movies released in the U.S. in the same year, the weight is 1; if in the 80*th* percentile, the weight is 0.9; and so on. Movies without revenue information are weighted by 0.1. Columns (1) to (4) in both panels of Table 6 report results using these weighted measures that are different in the length of the writer's history and the scope of the distributing studios.

Second, the Principle Component Analysis (PCA) is used to reduce multiple aspects of the writer's observable quality to a one-dimensional measure. Here, PCA is performed on WEXP, other writer characteristics and the writer's agency affiliation. The results are reported in Column (5) in both panels of Table 6.

Overall, these alternative measures confirm the basic results: 1) there is a non-monotonic relationship between the likelihood of a spec sale and the writer's observable quality; and 2) conditional on release, the

Table 6: Robustness Checks using Alternative Measures

(a) Probit Estimates for a Spec Sale (DV = SPEC)

	(1) $\text{WEXP}^{\text{5 yrs, major}}_{\text{weighted}}$	(2) $\text{WEXP}^{\text{all yrs, major}}_{\text{weighted}}$	(3) $\text{WEXP}^{\text{5 yrs, all}}_{\text{weighted}}$	(4) $\text{WEXP}^{\text{all yrs, all}}_{\text{weighted}}$	(5) WEXP_{pca}
Alt. Measure	-0.220***	-0.060***	-0.206***	-0.056***	-0.088***
	(0.060)	(0.022)	(0.057)	(0.021)	(0.015)
Alt. Measure ^{2}	0.056**	0.003**	0.050**	0.003**	0.019***
	(0.024)	(0.001)	(0.021)	(0.001)	(0.005)
Controls	Y	Y	Y	Y	Y
Pseudo R^2	0.097	0.093	0.097	0.093	0.098
N	1,834	1,834	1,834	1,834	1,834

(b) OLS Estimates for Movie Performance after Release (DV = log(US_BO))

	(1) $\text{WEXP}^{\text{5 yrs, major}}_{\text{weighted}}$	(2) $\text{WEXP}^{\text{all yrs, major}}_{\text{weighted}}$	(3) $\text{WEXP}^{\text{5 yrs, all}}_{\text{weighted}}$	(4) $\text{WEXP}^{\text{all yrs, all}}_{\text{weighted}}$	(5) WEXP_{pca}
SPEC	-0.086	-0.038	-0.087	-0.032	0.006
	(0.201)	(0.195)	(0.200)	(0.193)	(0.196)
Alt. Measure	-0.044	-0.085	-0.037	-0.077	0.060
	(0.181)	(0.081)	(0.180)	(0.075)	(0.174)
SPEC × Alt. Measure	0.513**	0.190**	0.492**	0.174**	0.170**
	(0.199)	(0.088	(0.196)	(0.081)	(0.076)
Controls	Y	Y	Y	Y	Y
Adj. R^2	0.602	0.580	0.601	0.578	0.580
N	191	191	191	191	191

Note: This table replicates Tables 3 and 4 using alternative measures of the writer's observable quality. Columns (1) to (4) use the (box-office-performance) weighted counts of the writer's major writing credits in the previous five years, major writing credits in the writer's entire history, writing credits for all movies in the previous five years, and writing credits for all movies in the writer's entire history. Column (5) uses a measure produced by the Principle Component Analysis. All columns in panel (a) use the same set of controls as in Column (1) in Table 3; all columns in panel (b) use the same set of controls as in Column (2) in Table 4; and marginal effects are reported. Standard errors are clustered at the writer level; and ***, **, and * are, respectively, significant levels of 1%, 5%, and 10%.

performances of specs and pitches exhibit increasing difference as the writer gets more experienced, and specs perform significantly better than pitches for top writers.

4.2 Alternative Explanations

Could the choice of sale stage be explained by the difference in writing costs? Different writers may have different writing costs, and even for the same writer, the cost may differ by idea. However, the observed patterns cannot be explained by the difference in writing costs alone, even though such cost heterogeneity is likely to exist.

First, one concern is that, instead of measuring the writer's observable quality, WEXP simply picks up the variation in the writer's average writing cost. For example, writers with a lower cost write more scripts and, hence, have more experience. If WEXP reflects only variation in the writing cost, we should

expect that performance measures (such as price, the likelihood of release and the movie's performance) are independent of WEXP for specs. This is because the writing cost is already sunk at the moment of sale (and, thus, should not affect price), and the cost alone should not affect the idea's quality. However, we find strong positive relationships between all of these performance measures and WEXP in the data.

Second, suppose that, given w, ideas differ in how costly they are to write up but not in their quality. Because the higher the cost, the more valuable are the interim feedback and having the buyer share the cost, the writer would choose ideas with higher costs to pitch and lower costs to spec, and the threshold in cost is monotone increasing with w. Then, conditional on release, the expected performance of a pitch should be higher than that of a spec for all w, and even more so for higher values of w. This prediction is also rejected by the data.

Pure information-acquisition story. Theoretically, an alternative model that can generate similar predictions is a pure information-acquisition story, in which pitching (as the mechanism of acquiring new information from the buyer before making the investment) is costly. In this alternative model, neither costly buyer participation nor differential IP protection levels is necessary. We can obtain the non-monotonicity result by manipulating the pitching cost: it needs to be substantial and decrease in w. Note that because we are comparing specs and pitches, this extra cost of pitching is what the writer does not need to incur if choosing to spec. This rules out most costs (e.g., search costs) that are likely to be substantial.

This is unlikely to be a convincing explanation of the data for the following reasons. First, we rarely hear writers complain about extra preparation they would have to do for pitching, while many express frustration at not being able to secure a meeting. Second, given the low probability of making a sale, the writer faces a high probability of wasting several months' time. This extra cost has to be unrealistically high in order to generate such a large proportion of specs in the data (55%). Third, if it is purely about information acquisition, writers associated with a big agency should be less likely to pitch because big agencies themselves have better information about demand. However, as is shown later, the data show the opposite.

Competing reasons for selling specs. Broadly speaking, the advantage of selling a later-stage idea is to obtain a larger share of the surplus. In addition to stronger IP protection, there are likely other reasons for the appropriability advantage, and their relative importance would depend on the institutional details of different markets. A specific reason is incorporated in the model both to make the argument concrete and because, in interviews with writers and agents, IP protection consistently arises as one of the most important considerations and is of broad interest in other contexts and to the literature.

It is important to recognize that the data cannot rule out the following competing reasons for speccing.

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First, specific to this context, the writer may prefer to spec because the likelihood of obtaining a sole credit—thus not having to share the credit bonus—is higher because the writer is guaranteed the authorship of two drafts rather than one.[30] This is more likely a competing reason for top writers, for whom the concern of expropriation is relatively small. It is much less important for relatively inexperienced writers, however, because the likelihood of a movie actually being produced is so slim that, according to people in the industry, the purchasing price for the various drafts is what the writer really goes after.

Second, for inexperienced writers, dynamic considerations outside the static model may also explain their high likelihood of spec sales. In a dynamic model, the writer may have an extra incentive to spec because it helps to accumulate experience, which, in turn, increases the chance of selling pitches in the future. In addition to the information asymmetry that forces inexperienced writers to sometimes over-invest in specs (which will be discussed later), the incentive to gain experience would also result in excessive speccing.

Alternative causal explanations for performance differences between specs and pitches. The model explains the better performance of specs through selection: the writer chooses better ideas to spec in the first place. There might be alternative causal explanations. For example, the buyer's early involvement during the scripting process might have a negative impact for pitches, though the opposite is arguably true. It could also be because pitches suffer from more-severe agency problems. A typical contract allows the buyer to terminate the project or to change the writer after each milestone. This staging arrangement is similar to what is commonly used in venture capital contracts (Gompers (1995)) and is designed mainly to alleviate agency problems. Despite the staging arrangement and reputation concerns, it could still be possible that pitches suffer more from moral hazard because the writer is guaranteed payment for the first draft as long as he delivers a craftsmanlike work.

These causal explanations suggest that pitches perform worse. However, to predict an increasing performance difference between specs and pitches, the buyer's negative influence (or the agency problem) not only must be sufficiently large but, more importantly, also must be increasingly negative to a sufficient extent as w increases. The latter condition seems rather implausible.

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[30]Conventionally, with a spec, the writer is typically hired for a revision, and with a pitch, he would be hired for the first draft. After that, the producer might or might not change the writing team.

5   Discussion

5.1   Social Optimum

With support from the data, this section comes back to the model and discusses its implications. In the context of the model, pitching is always more efficient than speccing because the former takes into account the buyer's knowledge before making the big investment. In the social optimum (illustrated in Figure 4), given w, the writer pitches if $\theta \geq q(w)$ and drops the idea otherwise, where $q(w)$ is the value of θ at which the total expected payoff from pitching equals the buyer's meeting cost.[31]

Evidently, an important source of inefficiency is the information asymmetry over θ prior to the meeting. Figure 5(a) illustrates the equilibrium outcome when the buyer also observes θ initially, and her meeting cost is not too high. Now, the buyer's meeting threshold for pitches, $m_p(w)$, depends on who the writer is. For $w \leq \bar{w}$, removing information asymmetry increases efficiency: some ideas can now be pitched rather than fully developed or dropped. For $w > \bar{w}$, some ideas are dropped because the buyer can screen ideas based on extra information. This may increase or decrease efficiency because some should be dropped (i.e, $\theta < q(w)$) but, previously, the seller did not internalize the buyer's meeting cost; and others should not be dropped (i.e., $q(w) < \theta < m_p(w)$), but the buyer is stricter than the social planner in meeting pitches.

In addition to information asymmetry, how profits are shared also affects efficiency. For example, the buyer is more reluctant to meet pitches than what is socially optimal (i.e., $m_p(w) > q(w)$) because she bears all the upfront cost while capturing only part of the profit. More interestingly, the seller over-invests in the best ideas (i.e., $\theta > r_0(w)$) because a further-developed idea grants a greater share of the surplus.
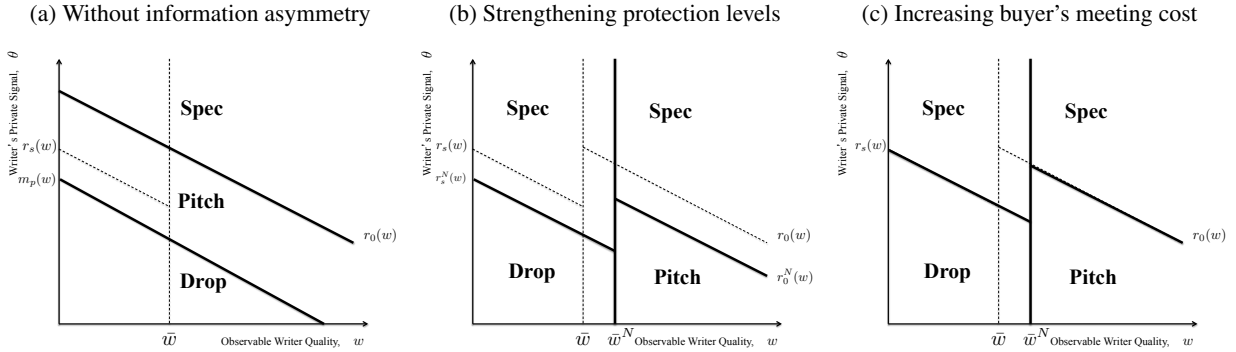
Figure 4: **Social Optimum**
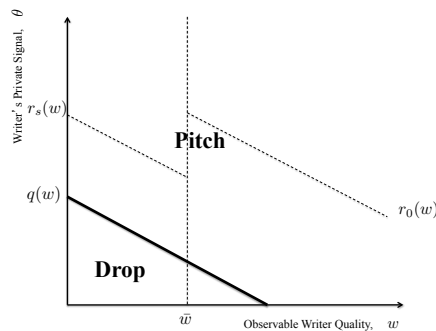
Notes: Given w, it is socially optimal to pitch if $\theta > q(w)$ and to drop the idea otherwise. The dashed lines in the background replicate the writer's equilibrium choice described in Figure 1. $q(w)$ is parallel to $r_0(w)$ and $r_s(w)$; and $q(w) < r_s(w)$.

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[31]The social planner maximizes the sum of the writer's and the buyer's expected payoffs, observing both w and θ.

Figure 5: **Comparative Statics of Equilibrium Outcome**

(a) Without information asymmetry

(b) Strengthening protection levels

(c) Increasing buyer's meeting cost

Notes: The solid lines and the texts describe the new equilibrium; and the dashed lines replicate the old equilibrium described in Figure 1. (a) allows the buyer to also observe θ prior to her meeting decisions; therefore, the buyer's meeting threshold $m_p(w)$ for pitches is now a function of w. Note that $m_p(w) > q(w)$, where $q(w)$ is the socially optimal threshold for pitching in Figure 4; (b) increases the protection levels (weakly) for both specs and pitches, and the increase for specs is at least as large as that for pitches. (c) increases the buyer's meeting cost.

A full-scale welfare analysis is beyond the scope of the paper. Based on simple comparative statics, the rest of this section focuses on the potential impacts of strengthening legal protection and the roles of intermediaries in the market for ideas.

5.2 Seller Innovation, Buyer Participation and the Strength of IP Protection

Many argue that a stronger IP protection increases the incentive to innovate. The model, however, implies that when transacting with the buyer is necessary for an idea's commercialization, there is no simple positive relationship between the strength of legal protection and the innovation incentive, or between the innovation incentive and efficiency. The following discusses potential effects of stronger protection from two perspectives: First, stronger protection may result directly in a greater share of the surplus for the writer when sales happen (i.e., higher λ's). Second, the likelihood of idea-theft lawsuits may increase when sales do not happen, and this essentially increases the buyer's meeting cost.

Figure 5(b) illustrates the comparative statics when stronger protection increases the writer's share of the surplus for both sale stages, and the increase for specs is at least as large as that for pitches (i.e., $\Delta\lambda_s \geq 0$, $\Delta\lambda_p \geq 0$ and $\Delta\lambda_s \geq \Delta\lambda_p$). For sellers who previously had difficulty selling earlier-stage ideas (i.e., $w < \bar{w}$), stronger IP protection provides more surplus and, hence, a stronger incentive to invest (i.e., $r_s^N(w) > r_s(w)$). This improves efficiency because the seller is generally more reluctant than the social planner to fully develop the idea. However, for sellers who were able to sell earlier-stage ideas (i.e., $w \geq \bar{w}$), efficiency may suffer. First, stronger IP protection results in later transfers (i.e., $r_0^N(w) > r_0(w)$), even though transacting

earlier is more efficient. Second, some of these sellers are now excluded from the earlier-stage market because of the dampened incentive from the buyer (i.e., $\bar{w}^N > \bar{w}$). Stronger seller protection discourages buyer participation here because her share of the surplus is reduced, and the expected quality of earlier-stage ideas is lower in the new equilibrium.

Because it is intrinsically hard to distinguish an unauthorized use of the disclosed idea from independent creation, buyers are often reluctant to provide access to just any seller because potential legal disputes not only hurt the buyer's reputation, but may also jeopardize similar projects that the buyer already has or may develop in the future. An increase in such risks essentially increases the buyer's meeting cost, and Figure 5(c) shows that this is largely bad for efficiency because of the heightened access barrier. The recent trend in the courts has been to strengthen the contract-law protection for idea sales (unauthorized use of the disclosed idea is a breach of the contract that is either written or implied).[32,33] Now, it is not only easier to push these claims forward, in parallel to copyright-infringement claims, but the incentive to sue is also greater because contract law allows for larger damage awards.[34] Despite the intention to empower small and independent idea sellers, there may be undesirable consequences because it dampens the buyer's incentive to participate, which, in turn, hurts the seller.[35]

5.3 Intermediaries in the Market for Ideas

Frictions in the market for ideas give rise to multiple roles that intermediaries can play. First, they help to reduce the information asymmetry between sellers and buyers. Under positive assortative matching, the association with a higher-quality intermediary, per se, signals a higher average writer quality (i.e., w);[36] and intermediaries are also better able to credibly convey the value of θ because buyers trust them more they do than individual sellers. Second, intermediaries can reduce the buyer's meeting cost. As experts, they reduce the buyer's evaluation costs, and, caring for their own reputation, they discourage meritless lawsuits from

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[32]In addition to the copyright law, which is a property-based IP regime, idea sales are also protected by the contract law: contracts, once established, require the buyer to compensate the seller if she uses the knowledge. Movie studios, TV networks and advertising agencies routinely refuse to listen to unsolicited ideas. Beyond these creative industries, in a study of 243 U.S. corporations, about half of the companies would examine unsolicited ideas only after receiving a signed waiver from the submitter (Udell (1990)).

[33]Nine out of eleven U.S. courts of appeals have established that these contract-based claims are no longer preempted by copyright law (Miller (2006)). Previously, breach-of-contract claims for idea theft were usually dismissed at the onset because they fall into the subject matter of copyright law.

[34]The Copyright Act prescribes that remedies for infringement are limited to either the copyright owner's actual damages and any additional profits of the infringer or to statutory damages. Larger damages, such as reasonable value of the defendants' use of the work, would be provided for through contract law (Brophy (2005)).

[35]After *Grosso v. Miramax*, the most recent ruling against federal preemption in California, observers of the entertainment industry noted a surge in idea-theft claims, as well as increasingly stringent waiver requirements by the studios. See "Idea Theft After Grosso—The Proliferation of Expensive and Burdensome Lawsuits" by Camilo Echavarria, available at "http://www.dwt.com/files/Uploads/Documents/Publications/FALL2007Winter.pdf."

[36]In Hollywood, the fixed 10% commission rate for agents prevents lower-quality writers from seeking to match with better agencies by giving up more rent. The positive assortative matching is confirmed by the data, at least for observable writer characteristics.

the seller. Third, intermediaries can help the seller to appropriate more rent, either because they reduce the buyer's expropriation incentives or because they have better information or a greater outside option. Finally, intermediaries can also provide useful information about demand, which reduces the value of obtaining information directly from the buyer through pitching.

These different roles affect the equilibrium outcome differently, and for each role, the impact may also be different for different writers. For example, reducing information asymmetry substantially increases inexperienced writers' ability to sell pitches, but restricts it for experienced writers because the buyer can now weed out the worst ideas (see the comparative statics in Figure 5(a)). In contrast, the role of strengthening the seller's ability to appropriate value makes the writer want to sell later, regardless of the writer type (see Figure 5(b)). Hypotheses 3 and 4 show that different roles often have opposite predicted effects on the likelihood of selling specs and the expected quality of these sales. The empirical analysis here is to let the data suggest which role is relatively more important, depending on the writer type. The prior is that the data should be more consistent with Hypothesis 4 for experienced writers than for inexperienced writers because the information-asymmetry issue is less of a problem in the former case.

Hypothesis 3. *Suppose that the intermediary reduces information asymmetry or reduces the buyer's meeting cost.*

(a) *Having an intermediary lowers the likelihood of a spec sale for writers with low observable quality, but increases (or does not affect) this likelihood for writers with high observable quality.*

(b) *Having an intermediary increases the average quality of specs for writers with low observable quality, but does not change the average quality of specs for writers with high observable quality. For writers who are good enough to pitch with or without the intermediary, having an intermediary either increases or does not affect the average quality of pitches.*

Hypothesis 4. *Suppose that the intermediary strengthens the seller's ability to appropriate rents or provides information on demand.*

(a) *Having an intermediary increases the likelihood of a spec sale regardless of the writer's observable quality.*

(b) *Having an intermediary lowers the average quality of specs regardless of the writer's observable quality. For writers who are good enough to pitch with or without the intermediary, having an intermediary lowers the average quality of pitches.*

In Hollywood, having an intermediary of some sort (agents, managers and sometimes lawyers) is more or less the norm. Being represented by the top five agencies, however, makes a big difference because of

their established reputation, large numbers of clients and frequent transactions with the studios. Therefore, the focus here is on the impacts an association with a big agency.

Table 7: **Effects of Big-Agency Affiliation**

(a) Linear Probability Model for the Likelihood of a Spec Sale (DV = SPEC)

	WEXP = 0	WEXP > 0
	(1)	(2)
WEXP		0.049
		(0.090)
BIGAGENT	-0.186**	0.109
	(0.078)	(0.188)
Controls	Y	Y
Writer FE	Y	Y
Adj. (Pseudo) R-squared	0.196	0.427
N	1,443	391

(b) Probit Model for the Likelihood of Release (DV = RELEASE)

	WEXP = 0		WEXP > 0	
	SPEC	PITCH	SPEC	PITCH
	(1)	(2)	(3)	(4)
WEXP			0.059**	0.060**
			(0.027)	(0.029)
BIGAGENT	0.062**	0.026	-0.121**	0.016
	(0.026)	(0.018)	(0.050)	(0.044)
Controls	Y	Y	Y	Y
N	850	593	144	247

Note: BIGAGENT indicates the affiliation with one of the five biggest agencies in Hollywood. The dependent variable in Panel (a) is SPEC. Column (1) uses a Probit model for all sales; and Columns (2) and (3) use a linear probability model with writer fixed effects. The dependent variable of Panel (b) is whether the sale is eventually released in the U.S.; and marginal effects of a Probit model are reported. All columns use the same set of controls as in Column (1) in Table 2, and cluster the standard errors at the writer level, except for the writer fixed-effects models. ***, **, and * are, respectively, significant levels of 1%, 5%, and 10%.

Panel (a) of Table 7 presents the results of a linear probability model for the likelihood of selling specs with writer fixed effects. To a certain extent, writer fixed effects control for the endogenous matching between the writer and the agency. Hence, the estimated results capture the treatment effects of an association with a big agency. Writers with zero credits are 18.6 percentage points more likely to sell a pitch if they are represented by a big agency. This result suggests that, for these writers, reputable agencies are very helpful in overcoming the access barrier to the buyer, which could be through reducing the information asymmetry or lowering the buyer's meeting cost (see Hypothesis 3). For relatively experienced writers, the effect of the big-agency association, though economically non-trivial, is not statistically significant. The sign of the coefficient, however, is consistent with the potential impacts of all roles.

Evidence from the likelihood of release—of specs in particular—further clarifies the story (panel (b) of Table 7). Here, we can proxy the idea's quality with the likelihood of release because the degree of uncertainty is comparable within each subsample. Interestingly, for experienced writers, big agencies are

actually associated with a lower average quality of specs. This is consistent with the explanation that, for these writers, the intermediaries are most relevant in improving the seller's bargaining power and providing feedback (see Hypothesis 4).[37] Similar to the comparative statics illustrated in Figure 5(b), these roles make the experienced writers want to sell later, which implies a lower average quality of specs. For inexperienced writers, big agencies are associated with a higher average quality of specs. This further confirms that for these writers, the most important role of an intermediary is to reduce the access barriers.[38]

6   Conclusion

Choosing when to sell an idea involves important trade-offs for the seller, and the choice also interacts with the buyer's incentive to acquire it. My model shows that, in equilibrium, the timing of the sale depends on the seller's observable experience and the quality of the idea. Inexperienced sellers cannot sell early-stage ideas and, thus, can only choose to develop the ideas fully or abandon them. By contrast, experienced sellers can attract buyers at any stage, and they choose to sell worse ideas sooner and to develop better ideas fully to sell it later. This implies a non-monotonic relationship between the likelihood of a later-stage sale and the seller's experience level. Data from the market for original movie ideas in Hollywood confirm this pattern.

An active market for ideas is important for industries in which established firms control key resources and novel ideas often come from outside the firm. The model is particularly relevant to markets that share the following features: The sellers vary in their track records, which are both observable and indicative of the idea's potential; the seller's ability to capture value increases as the idea is more fully developed; and buyers incur non-trivial costs to engage in the acquisition process (relative to the expected value of the idea). Examples include other creative industries such as book publishing, startups seeking financing, and individuals selling technical knowledge or inventions to established firms.

The paper has important implications for all participants in the market for ideas. First, unproven sellers, facing access barriers to potential buyers, will particularly benefit from credibly signaling the quality of their ideas. For example, they may be better off forming a team with more-established sellers, working with intermediaries that specialize in screening ideas (such as Hollywood agencies, book publishing agents, and venture capital firms), or investing in the idea to further resolve the uncertainty.

Second, because the quality of novel ideas is difficult to discern, it seems natural—and least risky—to invest in sellers with a proven track record. Moreover, competition for ideas from these sellers is likely to

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[37]Arguments such as 1) big agencies are likely to be associated with higher (unobservable) writer quality, and 2) big agencies have more resources to help to bring a project to market strengthen this conclusion because these effects work against the result.

[38]Note that the positive effect may also reflect the endogenous matching between writers and agents (that is, better writers are matched with better agencies). Writer fixed-effects models do not work in these regressions because of the lack of variation in BIGAGENCY after dividing the sales into different stages.

be significant, so it is temping to preempt rivals by acquiring these ideas early on. The results here suggest caution: the timing of sale is an important indication of quality. In particular, it seems prudent to stay away from options to buy early ideas coming from sellers who face no difficulty in selling at any time, or at least to take into account the lower expected quality when deciding whether to buy the idea and what price to pay.

Finally, the paper also has important welfare implications. Buyers are reluctant to meet unproven sellers because evaluating ideas costs both time and resources, and potential idea-theft disputes are costly. Therefore, unproven sellers are forced to either abandon or over-invest in ideas that are more efficient to sell at an earlier stage. It is generally tempting to strengthen intellectual-property protection in the hopes of incentivizing the creation of new ideas and facilitating their sales. In the context studied here, however, stronger protection may further diminish the market for ideas because buyers become more reluctant to meet unproven sellers who, in turn, abandon or over-invest in a greater number of projects. Smarter government intervention would aim to loosen the buyer's participation constraint. For example, such intervention would support intermediaries that help unproven sellers to credibly signal the quality of their work, reduce buyers' evaluation costs, and prevent opportunistic behaviors on both sides.[39]

References

Aghion, P. and J. Tirole (1994). The management of innovation. *The Quarterly Journal of Economics 109*(4), 1185–1209.

Allain, M.-L., E. Henry, and M. Kyle (2012). Inefficiencies in the sale of ideas: Theory and empirics. CEPR Discussion Paper No. DP8206.

Anton, J. J. and D. A. Yao (1994). Expropriation and inventions: Appropriable rents in the absence of property rights. *The American Economic Review 84*(1), 190–209.

Anton, J. J. and D. A. Yao (1995). Start-ups, spin-offs, and internal projects. *Journal of Law, Economics, & Organization 11*, 362–378.

Anton, J. J. and D. A. Yao (2002). The sale of ideas: Strategic disclosure, property rights, and contracting. *Review of Economic Studies 69*, 513–31.

Anton, J. J. and D. A. Yao (2008). Attracting skeptical buyers: Negotiating for intellectual property rights. *International Economic Review 49*(1), 319–348.

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[39]A recent example is an initiative by the National Health Council that matches university research proposals with potential funding sources. There, the priority score assigned by peer experts serves as a credible signal of the proposals' quality.

Arora, A. (1995). Licensing tacit knowledge: Intellectual property rights and the market for know-how. *Economics of Innovation and New Technology 4*, 41–60.

Arora, A., A. Fosfuri, and A. Gambardella (2001). *Markets for Technology: The Economics of Innovation and Corporate Strategy*. MIT Press, Cambridge, Mass.

Arora, A., A. Gambardella, L. Magazzini, and F. Pammolli (2009). A breath of fresh air? firm type, scale, scope, and selection effects in drug development. *Management Science 55*(10), 1638–1653.

Arrow, K. (1962). Economic welfare and the allocation of resources for invention. In R. Nelson (Ed.), *The Rate and Direction of Inventive Activity: Economic and Social Factors*. Princeton University Press.

Baccara, M. and R. Razin (2006). From thought to practice: Appropriation and endogenous market structure with imperfect intellectual property rights. Working paper, New York University.

Bagnoli, M. and T. Bergstrom (2005). Log-concave probability and its applications. *Economic Theory 26*, 445–469.

Bhattacharya, S. and J. R. Ritter (1983). Innovation and communication: Signalling with partial disclosure. *Review of Economic Studies 50*, 331–346.

Biais, B. and E. Perotti (2008). Entrepreneurs and new ideas. *RAND Journal of Economics 39*(4), 1105–1125.

Biglaiser, G. (1993). Middlemen as experts. *The RAND Journal of Economics 24*(2), 212–223.

Brophy, A. (2005). Note: Whose idea is it anyway? protecting idea purveyors and media producers after grosso v. miramax. *Cardozo Arts & Entertainment Law Journal 23*, 507–530.

Caves, R. E. (2000). *Creative Industries: Contracts between Art and Commerce*. Harvard University Press.

Chatterjee, S. and E. Rossi-Hansberg (2012). Spinoffs and the market for ideas. *International Economics Review 53*, 53–93. NBER Working Papers 13198.

Cohen, W., R. Nelson, and J. Walsh (2000). Protecting their intellectual assets: Appropriability conditions and why u.s. manufacturing firms patent (or not). NBER Working Paper Series 7552.

Corts, K. (2001). The strategic effects of vertical market structure: Common agency and divisionalization in the us motion picture industry. *Journal of Economics and Management Strategy 10*, 509–528.

Einav, L. (2007). Seasonality in the u.s. motion picture industry. *Rand Journal of Economics 38*, 127–145.

Elfenbein, D. W. (2007). Publications, patents, and the market for university inventions. *Journal of Economic Behavior & Organization 63*(4), 688–715.

Gallini, N. T. and R. A. Winter (1985). Licensing in the theory of innovation. *RAND Journal of Economics 16*, 237–25.

Gallini, N. T. and B. D. Wright (1990). Technology transfer under asymmetric information. *RAND Journal of Economic 21*(1), 147–160.

Gans, J. S., D. H. Hsu, and S. Stern (2002). When does start-up innovation spur the gale of creative destruction? *RAND Journal of Economics 33*(4), 571–586.

Gans, J. S., D. H. Hsu, and S. Stern (2008). The impact of uncertain intellectual property rights on the market for ideas: Evidence from patent grant delays. *Management Science 54*, 982–997.

Gans, J. S. and S. Stern (2003). The product market and the market for ideas: Commercialization strategies for technology entrepreneurs. *Research Policy 32*(2), 333–350.

Gans, J. S. and S. Stern (2010). Is there a market for ideas? *Industrial and Corporate Change 19*(3), 805–837.

Gil, R. and P. T. Spiller (2007). The organizational implications of creativity: the u.s. film industry in mid-xxth century. NBER working paper.

Goettler, R. and P. Leslie (2004). Cofinancing to manage risk in the motion picture industry. *Journal of Economics and Management Strategy 14*, 231–261.

Goetzmann, W. N., S. A. Ravid, and R. Sverdlove (2012, September). The pricing of soft and hard information: economic lessons from screenplay sales. *Journal of Cultural Economics*.

Gompers, P. A. (1995). Optimal investment, monitoring, and the staging of venture capital. *The Journal of Finance 50*(5), 1461–1489.

Hellmann, T. (2007a). The role of patents for bridging the science to market gap. *Journal of Economic Behavior & Organization 63*, 624–657.

Hellmann, T. (2007b). When do employees become entrepreneurs? *Management Science 53*(6), 919–933.

Hellmann, T. and E. Perotti (2011). Circulation of ideas: Firms versus markets. *Management Science 57*, 1813–1826.

Hsu, D. (2004). What do entrepreneurs pay for venture capital affiliation? *Journal of Finance 59*, 1805–44.

Jensen, R. A., J. G. Thursby, and M. C. Thursby (2003). The disclosure and licensing of university inventions. *International Journal of Industrial Organization 21*(9), 1271–1300.

Kamien, M. and Y. Tauman (1986, August). Fees versus royalties and the private value of a patent. *The Quarterly Journal of Economics 101*(3), 471–91.

Katz, M. and C. Shapiro (1986). How to license intangible property. *The Quarterly Journal of Economics 101*, 567–89.

Kuppuswamy, V. and C. Y. Baldwin (2013). Risky business: The impact of property rights on investment and revenue in the film industry. UNC Kenan-Flagler Research Paper No. 2013-2.

Lerner, J. and R. P. Merges (1998). The control of strategic alliances: An empirical analysis of biotechnology collaborations. *Journal of Industrial Organization 46*(2), 125–156.

Levin, R. C., A. K. Klevorick, R. R. Nelson, and S. G. Winter (1988). Appropriating the returns from industrial r&d. Cowles Foundation Discussion Papers 862.

Miller, A. R. (2006). Common law protection for products of the mind: an "idea" whose time has come. *Harvard Law Review 119*, 703–779.

Natividad, G. (2013). Multidivisional strategy and investment returns. *Journal of Economics & Management Strategy 22*, 594–616.

Pindyck, R. S. (1991). Irreversibility, uncertainty, and investment. *Journal of Economic Literature 29*, 1110–48.

Pisano, G. P. (1991). The governance of innovation: Vertical integration and collaborative arrangements in the biotechnology industry. *Research Policy 20*, 237–249.

Pisano, G. P. (1997). R&d performance, collaborative arrangements and the market for know-how: A test of the "lemons" hypothesis in biotechnology. Harvard Business School Working Paper.

Rajan, R. G. and L. Zingales (2001). The firm as a dedicated hierachy: a theory of the origin and growth of firms. *Quarterly Journal of Economics 116*, 805–851.

Roberts, K. and M. L. Weitzman (1981). Funding criteria for research, development, and exploratoin projects. *Econometrica 49*(5), 1261–1288.

Robinson, D. T. and T. E. Stuart (2007). Network effects in the governance of strategic alliances. *The Journal of Law, Economics, & Organization 23*, 242–273.

Sorenson, O. and D. M. Waguespack (2006). Social structure and exchange: Selfconfirming dynamics in hollywood. *Administrative Science Quarterly 51*, 560–589.

Teece, D. J. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy 15*(6), 285–305.

Udell, G. G. (1990). *Exploring the Innovation Process*. Innovation Institute.

Weinstein, M. (1998). Profit-sharing contracts in hollywood: evolution and analysis. *Journal of Legal Studies 27*, 67–112.